The supply of bank lending to small businesses

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Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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Chapter One

Introduction

1.1 Introduction

The aim of my research is to examine issues relating to the supply of credit to small and medium sized enterprises (SMEs) using a unique UK dataset containing loans and overdrafts from a major UK bank to its small business clients from 1998 until 2000[1].

The small business sector is of vital importance to the UK economy because it provides the seedbed that is necessary for nurturing the industries of the future (Bolton Report, 1971). Apart from helping secure the continuity of UK industry, the small business sector, as I will go on to demonstrate, provides a large proportion of UK employment and contributes towards GDP (Acs, Audretsch and Evans, 1991).

The dependence of this sector on banks for start up finance has been examined in the past (Bannock and Doran, 1991; National Economic Research Associates (NERA), 1990). This reliance on banks for finance emanates from the high risk of start-ups because they are considered too high risk for equity investors (Bank of England, 2001). Just under 20 percent of start-ups fail in their first year of trading and over 60 percent in the first 5 years (Barclay's Bank Information Service, 2000).

This reliance on the banking sector, in addition to the lack of a track record of business start-ups, gives rise to a myriad of problems. A well documented problem and one that surfaces repeatedly throughout my analysis, is the issue of how to evaluate the credit risk of business start-ups in view of their lack of a track record. A related question is how the bank formulates loan terms such as collateral and interest margins in such a way to ameliorate high risk, given the fact that start-ups lack a track record.

My analysis into the evaluation of credit risk is a timely one. The NERA report (1990) emphasised the need for better risk appraisal by banks. If the UK banking system moves in the same direction as the US Equal Opportunity Credit Act, it will become imperative in the future to use transparent and objective credit risk assessment instead of judgmental procedures if loan sanctioners need to defend their decisions before a court of law. Evidence by Deakins, Hussain and Ram (1992) for the UK and Overstreet and Kemp (1986) for the US, points to a disparity in the subjective decisions reached by loan sanctioners[2].

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[1] I define a Small and Medium Sized Enterprise (SME) using the European employment definition. According to this definition this category of business contains micro (1-9 employees), small and medium sized (10-50 employees) (Bank of England, 2001).

[2] This subjectivity was reflected in comments made by Dr. Charles Munn of the Chartered Institute of Bankers in Scotland attending the 1999 Credit Scoring and Credit Control Conference in Edinburgh. He indicated that before the advent of credit scoring, if the applicant had taken the time to polish his shoes, his chances of securing a loan were higher. Applicants wearing suede shoes were more likely to be rejected!

This is the basic context of my research; namely the supply of credit by the banks to small businesses, focusing on business start-ups, given the short or non-existent track record displayed by a business start up.

In this chapter I hope to present the context for my research into the supply of credit to SMEs. I will focus on the UK policy background and statistics where possible because my research uses UK data. I will show that issues such as the attenuation of the risk in lending to start-ups represent genuine UK policy concerns. The reduction of lending risk involved in bank lending to start-ups and the lack of adequate previous research into SME scorecards, provides a motivation for my development of a scorecard for first time business borrowers. I will also discuss the development of the UK debate into whether start-ups suffer from under-investment or a finance gap and explain in general terms why such under-investment is expected to arise. This debate provides the background for my research into why small business loans are turned down by a bank and whether preferential collateral and interest rate margins are given to second-period borrowers.

This chapter is structured as follows. In the next section, I will outline the motivations for my research and explain why such research is needed. In the section following this, I explain how my research has addressed issues presented in the first section and what contribution my research makes towards our understanding of bank finance to small businesses. The final section provides the structure of my overall research.

1.2 Why investigate the supply of bank credit to SMEs?

In this section I will give the motivations for my research and outline why the issue of bank lending to SMEs is worth exploring.

It is useful to set the context by providing some summary statistics on the value of the SME sector to the UK economy. Essentially, a healthy SME base is a positive indicator of the wellbeing of domestic industry. The Bolton Report (1971) refers to the 'seedbed' function of small businesses where a healthy small business base is necessary in order to ensure that the stock of large indigenous firms grows.

A healthy SME base is also essential for job creation. Acs, Audretsch and Evans (1991), in an international survey, reported that the increase in self-employment since the 1960's continued to grow steadily in the UK.

Recent statistics from the Department of Trade and Industry are shown in **Table 1.1**. According to these statistics for the UK, the SME sector is responsible for 99 percent of all enterprises, 44 percent of all employment in industry and 37 percent of corporate turnover. Small businesses are therefore a very important component of the UK economy.

Small businesses are not only a vital component of the UK economy but they are also very reliant on their banks for the provision of finance (Bannock and Doran, 1991; NERA Report, 1990). According to Bannock and Doran (1991), reporting the number of venture capital investments for the major UK venture capital provider 3i, 3i indicated that only 35 of the 989 investments in venture capital were for business start-ups. This means that the vast majority of start-ups must recourse to a bank or some other financial source such as family or business angel for finance. This is corroborated by a recent Bank of England Report stating that banks represented the single largest source of finance for business, high-technology start-ups where 61 percent of start-up capital originates from bank funds (Bank of England, 2001). Venture capital represents a mere 1 percent of the start-up finance of these businesses. There would not be a great difficulty lending to SMEs if these small businesses were well endowed with initial wealth to offer as collateral, in which case the bank would have its investment fully covered in the event of default. If for instance, business start-ups did not have sufficient initial collateralisible wealth, the result would be under-investment by banks and therefore business projects would be carried out in a sub-optimal way.

There is conflicting evidence as to whether there is under-investment in small businesses. Tentative evidence from Hughes (1992) suggests that under-investment is manifested by smaller UK businesses. He investigated the breakdown of finance for UK limited companies. According to Hughes, smaller companies had a lower ratio of fixed to total assets compared to larger companies (31.5 percent viz. 44.4 percent). They also had comparatively more of their assets is tied up in trade debts and other debtors than larger companies (37.9 percent viz. 23.6 percent). The implication of their different asset structure means that they have comparatively fewer assets to offer as collateral to a creditor. This could lead to underfunding of the small business sector. Also they are more likely than large companies to experience shortages in working capital because a comparatively higher proportion of their assets are tied up in trade and other debtors. The conjecture that small businesses experience working capital problems is seen in the fact that 35.3 percent of their current liabilities are owing to trade and other creditors, compared with 23.6 percent of the current liabilities of their larger counterparts. Petersen and Rajan (1994) have pointed out that trade credit is the most expensive form of business funding.

The NERA report (1990) dismisses the notion that UK start-ups are underfunded. Their task was to evaluate the Loan Guarantee Scheme (LGS) that was introduced in 1981 on the recommendation of the Wilson Committee (1979).

The LGS was created to address the perceived gap in the availability of loan finance for smaller firms. Under the LGS the government provides a guarantee to the banks of loans to potentially viable small firms that would otherwise not receive debt finance on commercial terms because they lack adequate assets to offer as collateral. Only 0.6 percent of all small firms were assisted by this facility (Storey, 1994).

The NERA report concluded that the increase in bank lending to small businesses by the end of the 1980's meant that the role of the LGS was becoming more unnecessary. They urged banks to try reducing their small business default rates instead, via better appraisal of loans. This view that banks need to refine their appraisal systems rather than increase the amount of lending to SME as suggested by the NERA report is echoed by Storey (1994).

He states that;

'The central issue is the making of good decisions, and not either the scale of resources provided to the small business sector, or the fact that some businesses are excluded (probably quite correctly) from access to loans'[3].

A policy shift is evident from the Government taking responsibility for a perceived lack of start-up assets towards a plea for business lenders to improve their risk appraisal procedures. This latter policy would favour better appraisal systems in the form of more efficient credit scoring. It also puts the onus on the bank to improve its information on small businesses but does not suggest how this is to be achieved.

This need to improve the risk appraisal of loans to business start-ups, represents one thrust of my research. Due to the inapplicability of the existing credit scoring models to the scoring of small business start-ups, there is a research gap in this area that my analysis attempts to fill.

The process of evaluating small business loans using credit-scoring techniques is still relatively under developed. Progress here is not as advanced as the scoring of consumers for credit or store cards. The latter two applications of scoring have been in existence since the 1980's (Thomas, 1998). Despite the development of the zeta-score by Altman (1977) for the scoring of large businesses, this scoring system is not appropriate for SMEs for a number of reasons. Firstly, the quality of accounting information required to construct financial ratios is of a standard many business start-ups cannot hope to supply. Nayek and Greenfield (1994) examined 200 micro-businesses in the UK West Midlands and were struck by the lack of financial awareness of the entrepreneurs questioned in their survey. Only 34 percent used any form of budgeting while the majority of respondents kept a mental note only of financial information. In fact, in businesses with less than 10 employees (micro-enterprises) the formal monitoring of profits takes place in only a third. Moreover, 16 percent of enterprises with debtors kept no debtor records.

[3] P.246 Storey, D., 1994. 'Understanding the small business sector'. Routledge: London

For example, cash flow variables, require a highly developed in-house accounting system. These have been shown to be predictive in numerous business failure studies, (Bahnson and Bartley, 1992; Gilbert et al., 1990; Platt and Platt, 1990; Platt et al., 1994, Schellenger and Cross, 1994; Taffler, 1999) but if the findings of Nayek and Greenfield (1994) are indicative, the likelihood of obtaining satisfactory cash-flow variables is low.

A more salient reason for the inapplicability of the zeta-score for small businesses, is its concentration on financial information to the exclusion of what Cressy (1996c) refers to as 'human capital' characteristics. Such characteristics include variables such as the number of years work experience the entrepreneur has.

In view of the need for better risk appraisal by banks as highlighted in the NERA report (1990) and the inapplicability of existing business risk appraisal models to business start-ups, my attempt to develop a scorecard for start up loans is both timely and appropriate.

However, in addition to looking at the appraisal of start-up loans, it is also useful to establish whether banks are under investing in first-period business borrowers compared to second-period borrowers. The issue of under-investment in first-period business borrowers arises because first period borrowers lack a sufficiently long track record. If banks are more likely to turn down businesses without a credit history when they apply for finance, all things equal, then under-investment in business start-ups is a possible consequence of higher rejection rates from ab initio borrowers. Another way of looking at this question is to compare the collateral levels required from new and existing businesses in order to see whether new businesses are required to provide more collateral when controlling for the size of the loan. Finally, it is possible to formulate the track record question in terms of the cost of credit. In other words, I set out to establish whether the bank charges second period borrowers more for their finance than ab initio borrowers.

1.3 Contribution of my research to knowledge of SME bank finance

With this research aim of investigating the supply of credit to SMEs in mind, I constructed several application scorecards that used the information generated from over 7,000 first time applications by business start-ups. The aim of these scorecards was to predict the risk of default of these businesses at least 6 months later using all in-house information about the borrowers' credit histories[4].

[4] One way a bank can enhance its risk appraisal procedure and compensate for the lack of a business start-up's track record is by using any in-house credit history it has about the borrower in its credit scoring model. This information includes any credit history the bank has recorded on the entrepreneur's current accounts, credit card accounts or other accounts conveying information about the borrower's credit status.

My study is the first to use a relatively large scale UK dataset to estimate the probability of default for business start-ups. Up to now studies have merely estimated the probability of bankruptcy for large, publicly quoted firms (Gilbert et al., 1990; Mossman, 1998; Laurence and Arshadi, 1995; Bahnson and Bartley, 1992; Altman et. al., 1994). The most similar published study on small businesses is by Leonard (1992) but he uses a much smaller dataset (283 applications) and estimates the probability that a small business has its loan application accepted, rather than using a default proxy as the explanatory variable.

I find that it is possible to construct a business scorecard for first-period business loans but that out-of-sample prediction is poor unless the cost of misclassifying a borrower who turns out to be bad is very high.

The other focus of my research is on the way in which the bank formulates the credit terms such as interest margin, collateral amount and the rejection rate. These issues are interesting because while they are relatively well covered in the theoretical literature, there is a paucity of appropriate data that researchers can use to test the predictions of the models[5]. For this reason, empirical work concentrates on the US National Survey of Small Business Finance dataset used by Petersen and Rajan (1994), Berger and Udell (1995) and Cole (1998). A non-public UK National Westminster Bank dataset used by Cressy in numerous analyses (Cressy, 1996a; Cressy, 1996b; Cressy, 1996c; Cressy and Toivanen, 1998) represents the other main source of data for small business empirical analyses. The only other source of data is to be found in the commercial databases of business data such as FAME[6]. Commercial datasets are lacking however in potentially rich variables such as entrepreneur age and work experience because they only contain the abbreviated financial statements of the contributing SMEs. Commercial data are therefore highly aggregated and do not supply details regarding the business principals.

The reason I have highlighted the scarcity of information on small businesses, is to underline the fact that I was fortunate to have access to a private database of UK start up loans from a major UK retail bank for my research. This permitted me to investigate several questions relating to loan terms that have caused difficulty in the past because of data availability problems.

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[5] Chapter 2 outlines these theoretical models by Besanko and Thakor (1987a and 1987b), Bester (1985), Stiglitz and Weiss (1981, Jaffee and Russell (1976), Evans and Jovanovic (1989), Petersen and Rajan (1995) and de Meza and Southey (1996)

[6] FAME stands for Forecasting Analysis Modelling Environment and contains data on SMEs. Compustat data is used in research by Gilbert et al. (1990), Platt and Platt (1987), Lo (1986) and Mossman et al.(1998) but since the businesses on the latter database are listed on the Stock Exchange or are established firms, data from Compustat cannot be used for research on small or start-up businesses.

The first issue I analysed with regard to the formulation of loan terms was what factors determine the interest margin on small business loans. In so doing, I was particularly interested in determining whether businesses with previous credit histories were extended finance on more favourable terms than businesses that had no credit history with the bank. My contribution to the existing work in this area was to investigate whether small businesses are 'informationally captured' i.e. they must pay more for second-period finance because their credit history cannot be observed by another bank and is therefore private information that is retained by the original lending bank. There is an existing literature in this area focusing on large firms (Hoshi et al., 1990b; Shockley and Thakor, 1993; Billet, Flannery and Garfinkel 1995). There is also literature dealing with the loan terms extended to US firms (Petersen and Rajan, 1994; Berger and Udell, 1995). However, this is the first UK analysis of its kind to look specifically at the cost of second period finance. I found that second period finance is more expensive than first-period finance, where expense is measured, in terms of the magnitude of the interest margin.

The next issue that my research aimed to address is which factors motivate a bank to reject a small business loan. I also had limited data on business borrowers (for over 3,000 loans) who had their loan applications turned down. Some of these rejected borrowers already had taken out loans with the bank. The question I wanted to investigate was what caused the bank to reject a loan, given that it could already have loaned to a business in the past. Leonard (1992) and Cole (1998) tackled similar questions. The difference between my research and existing research in this area, is that my research is the first UK analysis to use loan rejection as the response variable. Unlike Cole (1998), I also endeavour to give an ex post explanation of my findings that businesses who ask for more money and where less collateral is transferred to the bank,

have a higher chance of being turned down. My simple 'E-T' model is intended to put the loan rejection decision in a rationing context and to suggest a possible direction for future research[7].

The final contribution of my research is to investigate the difference in the collateral levels of start-up businesses and of established businesses[8]. In so doing, I use data on over 9,000 existing businesses that banked with this UK lender. What is unique about this particular analysis is that up to now it has been impossible, due to data restrictions, to measure the level of collateral because collateral has taken the form of a binary *'yes-no'* type variable. In other

[7] Different theories of credit rationing can be interpreted simultaneously. Credit rationing theories tend to describe one type of credit rationing and disregard any other types. My explanation of the loan rejection decision suggests that two forms or more of credit rationing can operate simultaneously.
[8] A version of this analysis is published in Small Business Economics, May 2002

words, it has been possible to indicate whether collateral has been taken on a loan but the level of collateral has remained unknown. I found that there is not much disparity in the collateral terms charged business start-ups and existing businesses when possible anomalies in the database had been considered taken into account[9].

Overall, my research has aimed to use my unique data on UK small business loans to explore issues concerning the supply of credit to small businesses, with particular emphasis on start-ups.

It is unfortunate that I had not a sufficiently long time window that would have allowed me construct some longitudinal analyses. I could then have taken general UK economic conditions into account such as the exchange rate regime, seasonal variations in expenditure or purchasing trends. The report by Barclay's Bank Information Service (2001) indicates that economic conditions are a major factor behind small business default rates. Additionally, a loan repayment performance period of more than 6-months would have allowed me estimate the time to failure of start-ups using the data generated from borrower application forms. However, in spite of the cross-sectional nature of the data and in the knowledge that there is no available longitudinal data on small firms offering the same depth of disagregated data, I have shown that I addressed several important issues relating to the supply of credit to small UK businesses.

1.4 Structure of the thesis

The thesis consists of three parts.

1.41 Part One: The literature

In this first part I review the literature of credit scoring and information asymmetries as separate units. I have had to organise the mutually exclusive literatures relating to credit scoring and information asymmetries into separate chapters. It was not possible to reconcile these two literatures because the science of credit scoring is predictive and the theories of lending are interpretative. However, where there was any overlap, I have tried to cross-reference between the two. **Chapter Two** presents the literature of credit contracts (information asymmetries and the role of the contract variables). **Chapter Three** outlines the methods I use in constructing my scorecards and **Chapter Four** presents the credit scoring literature.

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[9] A possibility for future research would be to investigate whether the distinction between start-ups and existing businesses are equally blurred when controlling for the relative wealth of both types of businesses. If start-ups had to post a comparatively higher level of their wealth in order to secure a

1.42 Part Two: The data extraction

Chapter Five details the data extraction process. Due to the complexity of the data, I thought it useful to include this chapter. By including this chapter I highlight certain decisions I had to take regarding the aggregation of the data when converting the data from a relational database to flat file format.

1.43 Part Three: The empirical chapters

Following the data extraction chapter are four self-contained empirical chapters. Each chapter contains a brief overview of the relevant literature in order to highlight the research question that the chapter addresses, before I outline and present my empirical results.

Chapter Six presents, compares and contrasts the results of several SME scorecards that I estimated. **Chapter Seven** deals with the price of credit in the form of interest margins.

Chapter Eight investigates which variables influence the sanctioner's decision to accept or reject a small business applicant. This research question is placed in a credit constraints framework and emphasis is placed on the role of information asymmetries. **Chapter Nine** represents an analysis on collateral. **Chapter Ten** concludes with a summary of my main findings and the policy implications of my results.

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loan than an existing business, it would not have the same proportion of residual collateral to secure an additional loan with another or the same bank.

Table 1.1 Number of Enterprises, Employment and Turnover in the private sector
(by size of enterprise and industry sector, 2000)

Values

	Number of enterprises	Employment	Turnover
		('000)	(£ million)
SME*	3,690,780	9,650	756,607
Non-SME	31,830	12,482	1,277,122
All	3,722,610	22,132	2,033,728

Percent

	Number of enterprises	Employment	Turnover
SME	99	44	37
Non-SME	1	56	63
All	100	100	100

* SME is defined as sole trader or business with up to 50 employees

Source: Own estimates from Department of Trade and Industry, 2001. *'http:/www.sbs.gov.uk/statistics'*

Chapter Two

The theoretical literature on small business finance

2.1 Introduction

The aim of this chapter is to review the literature providing the theoretical background to issues relating to small business loan finance. This chapter therefore serves as a background chapter to the subsequent empirical chapters **Chapter 7**, **Chapter 8** and **Chapter 9**.

One way of presenting the literature is to extract the most meaningful arguments from the individual contributions (those that bear relevance to my empirical work). However, extracting the meaningful arguments involves, to some degree, lifting these arguments from the mathematical context in which they are presented. Since many of the arguments are derived from mathematical models, there is a danger that lifting these conclusions without providing enough of the mathematical background might reduce the impact of these conclusions.

Therefore, the approach I use in this chapter is to explain first in a non-mathematical way the findings of the scientific paper that have relevance for my research before presenting the core algebraic arguments of these papers. To some extent, this approach means pre-empting the conclusions of the papers before describing the context. However despite the flaws of this approach, it permits me to present the literature in a more user friendly way and means that the reader can relate this paper to the ones that have gone before.

I use this approach because it is not my aim to replicate these scientific papers. The aim of my review of the literature is to interpret and find connections between different contributors.

The structure of this chapter is as follows. The first section provides basic background on what is meant by a bank loan in the contract literature and introduces some basic terminology. The next section reviews the literature on the significance of credit constraints and business-bank relationships. The next section gives an overview of the literature. In the section following this I provide a more exhaustive and mathematical review of the individual models. The final section concludes with a summary of the main arguments.

2.2 Defining a loan contract

This section explains some of the fundamental concepts of bank lending to small firms including what is meant by a loan contract, imperfect information and the reason a bank would wish to maintain close, exclusive links with a business borrower.

Jaffee and Stiglitz (1990) refer to a loan contract as a promise of repayment. Because payment occurs at a future time and promises can be broken, the lender cannot be certain that he will be reimbursed.

If credit markets were like normal Walrasian markets with supply equalling demand at equilibrium prices (interest rates) there would be little need for the literature on credit rationing. However, the 'market for promises', as Jaffee and Stiglitz describe it, cannot be described by the standard supply and demand model. This market is typically in disequilibrium where applications for credit are frequently not satisfied. Jaffee and Stiglitz argue that:

'The special nature of credit markets is most evident in the case of credit rationing, where borrowers are denied credit even though they are willing to pay the market interest rate (or more) while apparently similar borrowers do obtain credit'[1].

What is the reason for the failure of the standard market model to explain the market for credit? Jaffee and Stiglitz argue that the risk of borrower default is not a sufficient condition for market failure because the uncertainty of repayment can be dealt with under the standard model. What makes the market for credit inefficient is the possible existence of *'imperfect information'*. Imperfect information of any kind means that the borrower, lender or both parties to the loan contract have unequal access to all the available information. The term *'asymmetric information'* on the other hand, implies that one of the parties (usually the borrower) has access to information that is unavailable to the lender.

Now we move on to defining the loan contract itself. The loan contract is characterised by the fact that a bank can only claim back from the borrower what it has lent but that it has no right to any of the excess profits arising from the successful outcome of the entrepreneur's project. In other words, the most a bank can demand is his original loan principal plus the interest on the principal while the borrower can enjoy all profits over and above the borrowed capital. This is an important distinction to make because it shapes the borrower's and lender's risk preference.

Storey (1994) defines the above as follows. The probability of the success of the start-up is defined as p, the borrowed capital in the form of a loan is defined as L and the interest rate is r. If the start-up is successful it will yield returns Y and if it fails it yields zero returns. The expected gain to the firm which borrows from the bank is:

$E(\pi)^F = p\,[\,Y - (1+i)L\,]$

[1] P.839 Jaffee and Stiglitz (1990)

where $E(\pi)^F$ is the expected profit of the firm. On the other hand, the expected return to the bank $E(\pi)^B$ is only $p\,[(1 + i)L\,]$. This is because the bank is not an equity shareholder in the business and therefore cannot hope to benefit from any excess profits.

Now assume that there are two discrete outcomes that the borrower can produce; a good outcome, $(Y_{a,})$ that is higher than the bad outcome, (Y_b). The probabilities P^a and P^b denote the likelihood of these outcomes arising where P^a and P^b sum to 1. The expected value of the bank loan is therefore $E(L) = (P^a * (Y_a) + P^b * (Y_b))$.

Jaffee and Stiglitz assume that there is a mean preserving spread such that the expected return from both these outcomes is the same. In other words, the higher return carries a lower probability and the lower return carries a higher probability in such a way that the expected return $E(L)$ is the same.

Now that I have described the basic fundamentals of the loan contract, I am now going to describe how the firm defaults using the same nomenclature. If the value of the repayments to the bank, L, is less than the good outcome, Y_a, then the loan is always repaid because the borrower has always got the minimum amount with which to repay the bank. You will recall that the good outcome, Y_a, occurs with higher certainty but is less than the income generated by the bad outcome, Y_b. If the value of the loan repayments, L, is greater than the bad outcome, Y_a, then the borrower always defaults because he can never generate a high enough return from his project with which to repay the bank. In other words, the bad outcome, Y_b, is the maximum amount he could expect to earn from his project. If the borrowed amount falls between the bad outcome, Y_b, and the good outcome, Y_a, then the expected repayment is $P^a (1 + r)L + P^b Y_b$. This implies that the full amount borrowed $(1 + r)L$ is repaid with probability P^a, and whatever the available funds from the project when the bad outcome occurs are gained, with probability P^b.

The format of the expected payment to the bank $P^a (1 + r)L + P^b Y_b$ illustrates two points. Firstly, as the interest rate r rises, ceteris paribus, the expected repayment to the bank rises because the term $P^a (1 + r)L$ increases. However, if uncertainty rises and the probability of the bad outcome P^b increases because the entrepreneur focuses his attention on producing the bad outcome, the expected repayment to the bank decreases. Consequently, the bank prefers a higher interest rate and a project offering low uncertainty while the borrower prefers a lower interest rate and high uncertainty.

I will now explain the risk preference of the bank and borrower using an example to make it clearer. Imagine that the good outcome offers £20,000 and the bad outcome £50,000. Given the assumption of the mean preserving spread, the good outcome has a 71.4 percent chance of occurring and the bad outcome a 28.6 percent chance. The expected return from both projects is therefore approximately £14,300[2]. The entrepreneur has an incentive to prefer the higher income risky project despite its less certain outcome because he can then retain all profits in excess of the value of the loan repayments. Imagine that the bank sets the loan value, *L*, at £15,000 with an interest rate of 20 percent. The loan repayments on a principal of £15,000 would amount to £18,000. The entrepreneur knows that if he chooses the high-risk strategy, *b*, he could earn £50,000 and thereby earn himself a net return of £32,000 after repayments of £18,000 had been deducted. He would therefore have an incentive to take a gamble and pursue the higher risk project. If, on the other hand, he pursued the low risk project he could earn £20,000 which only leaves him a net return of £2,000 after the loan repayments have been taken into account.

The bank would prefer a situation of low uncertainty and high interest rates in order to have a higher likelihood of the good outcome arising and the high interest rate maximises its expected return because its expected repayments $(1 + r) L$ increase accordingly. On the other hand, the borrower is prepared to gamble and would prefer a higher degree of uncertainty accompanied by a lower interest rate. The bank therefore has to use some type of incentive such as collateral to induce the borrower to work harder to produce the good outcome. It is not enough for the lender to rely on the interest rate. As Jaffee and Stiglitz point out, the lender must resort to using other non-price terms in order to reduce the likelihood of borrower default of which collateral is the most important mechanism.

Another way besides collateral of reducing the risk of default is the use of exclusive business-bank relationships. Business-bank relationships are explored more fully in the empirical **Chapter 7** on interest rates and **Chapter 8** on the loan sanctioner's decision. The reasons a bank would want to promote close ties with a borrower are manifold. Firstly, there are fixed or 'sunk' appraisal costs in making a loan that a bank can only hope to recoup over time. For example, application data and reports on the entrepreneur's creditworthiness collected by a loan sanctioner at $time_t$ can be used at $time_{t+1}$ to inform decisions on the borrower's creditworthiness for a rollover (follow-on) loan. This high overhead cost incurred when making the initial loan can be amortised over subsequent loans. Also the lender may specialise in certain industries where it has already acquired a portfolio of similar firms. For example if a bank specialises in lending to the farming community it may

[2] Because of rounding, an approximation is given. The low risk outcome actually has an expected return of £14,280 and the high-risk outcome of £14,300

be more aware of the financial pressures facing the farming sector. Therefore, a reason for concentrating borrowing in the hands of one lender is the cost savings they entail.

A further reason why a bank would wish the borrower to concentrate bank borrowing in the hands of one lender is that it allows the bank an overview of all the entrepreneur's borrowings. According to Jaffee and Stiglitz, many loan contracts contain the clause that if any one loan is in default, all the other loans should automatically be flagged as problem loans. It follows that if the bank holds all the entrepreneur's borrowings, he is well informed on each of the entrepreneur's loans and does not need to liase with other banks regarding the borrower's creditworthiness.

Another justification for close ties with the borrower is the risk of adverse selection. Akerlof (1970) documented this effect for the first time by using the analogy of the market for second hand cars. In a business borrowing context, once a first-time business borrower has been vetted by a bank and been granted a loan in one period, other competitor banks would be wary if they were approached by the business for a second period loan. They cannot observe the quality of the borrower but would infer that the motivation for the borrower leaving his original lender must be due to his poor creditworthiness. If a borrower approaches a second bank, it therefore sends a signal to the second bank that his quality is poor and hence he was compelled to move his custom to another bank. There is therefore more competition for a first-time borrower (ex ante competition) than for a second period borrower (ex post competition) if the borrower's credit status cannot be observed (under private information).

2.3 The nature of credit rationing

The literature on credit constraints dates back to the seminal paper by Jaffee and Russell (1976). Since then there has been a variety of research into the theory behind credit constraints, most of which derives from the 1980's.

The aim of this section is to provide the theoretical background for my empirical analyses into issues such as the loan sanctioner's decision (**Chapter 8**), the role of a borrower's reputation (**Chapter 7**) and the role of collateral (**Chapter 9**). These theoretical papers have all influenced the important empirical papers in the literature and which I have referenced in my empirical chapters. The same views shaping the seminal theoretical paper by Petersen and Rajan (1995) are reflected in the empirical papers by Petersen and Rajan (1994) and Berger and Udell (1995) both of which investigate the role of business-bank relationships in influencing the price of credit. The Petersen and Rajan (1995) model also influences the empirical analysis by Cole (1998) into the availability of credit. These key empirical papers are central to my analyses on the price of credit (**Chapter 7**) and the availability of credit (**Chapter 8**). The theoretical paper by Evans and Jovanovic (1989) has shaped much of the empirical and theoretical work by Cressy on credit constraints (Cressy, 1996a; Cressy and Toivanen, 2001; Cressy, 1996c) which are referred to in **Chapter 8** and **Chapter 9**.

In general, credit rationing takes place when information about the credit status of young or small firms without a track record is low. Therefore the bank is forced to minimise its exposure to such firms. Otherwise, the likely high default rates of such firms would bring about high losses for the bank on its lending portfolio. The reason a bank would nevertheless be keen to lend to such high-risk firms is that it must keep introducing new business to its lending portfolio, even if this implies higher risk loans.

All theories agree on credit rationing being employed by banks as a risk reduction instrument. How the bank goes about reducing its exposure to small business loans is a separate issue. The bank can do this is two ways. It can decide to lend to all businesses but only grant loans falling short of what the borrower has requested. The other way a bank can reduce its exposure to a high-risk business sector is to have a higher rejection rate on high-risk loans than it would otherwise have if there were more available information on the quality of these firms. The bank can either hold a non-discriminative lottery or a discriminative screening process in order to select firms for financing. It will therefore deem some firms to be eligible for finance and reject the remaining firms. The bank rations the credit it would otherwise have allocated and this credit rationing arises from imperfections in the level or quality of information about these firms.

It should therefore be evident that there are therefore two ways in which a bank can reduce its risk exposure to a high-risk sector. This is an important distinction because it is one fundamental difference in the way past research has interpreted credit rationing.

There are several ways in which theorists can model or interpret credit rationing. Although each model is unique and of course there are different assumptions among models from the same broad group, there is a common denominator shared by groups of models. The rationing theories can be broadly categorised as follows.

Some theories describe *'transitional'*, or Type I rationing, where the amount of first-period finance extended to the entrepreneur is less than the amount demanded by the entrepreneur'[3]. Examples of papers that adopt a *'transitional'* interpretation of rationing are the papers by Jaffee and Russell (1976) and Petersen and Rajan (1995). The bank performs this type of rationing in order to reduce its exposure to the firm. It anticipates that the probability that the firm will repay its loan will be increased if the business has a relatively small loan to repay. According to models depicting this type of rationing, the entrepreneur's application for finance is not rejected. Instead, the bank decides to under invest in the firm occurs in the first period and then comply with the full request for finance once the borrower's credit status becomes known. *'Transitional'* credit rationing is a two period phenomenon where rationing occurs in the first period. Finance is essentially staggered over both periods. In *'transitional credit rationing'* the market for loans does not clear in the first period when the loans are granted to the firms. The demand for loans exceeds the supply of loans. It is only in the second period, when the creditworthiness of firms becomes known to the bank, that good firms are supplied with the remainder of the loan that they requested. By this time bad firms have already defaulted. By the time the first period has elapsed, the bank is able to fully satisfy the demand for finance. Besanko and Thakor (1987a) describe this type of credit rationing as follows;

'Rationing emerges (in transitional credit rationing models) because restricted loan sizes, resulting in excess demand induce a lower fraction of defaults. ....the rationing that occurs is likely to be transitory since default is an ex post choice of the borrower and reputations therefore develop'[4].

Other theories describe *'equilibrium'*, or Type II, rationing where some loans are allocated on a lottery basis while others are fully rejected (Stiglitz and Weiss, 1981; Bester, 1985; Besanko and Thakor, 1987a; Besanko and Thakor, 1987b). A bank sometimes performs *'equilibrium'* rationing in order to induce entrepreneurs to choose a combination of interest margin and collateral that is compatible with their risk type. This strategy is known as *'self-selection'* by borrowers. For example, the bank may offer lower risk entrepreneurs lower interest margins coupled with higher collateral requirements. In order to deter high-risk entrepreneurs from choosing this contract, the bank rations loans that are directed at low-risk borrowers[5].

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[3] Cressy (1999) uses the terms Type I rationing to describe *'transitional rationing'* and Type II rationing to describe *'equilibrium rationing'*

[4] P.682 Besanko and Thakor (1987)

[5] In my own simple model of credit constraints which draws from the two approaches *'equilibrium credit rationing'* models and *'transitional credit rationing'* models, it is assumed that the amount of the loan both influences the decision to accept or decline the loan (*'equilibrium credit rationing'*). Furthermore, the bank would like to minimise its exposure to first time borrowers by lending less than the equilibrium amount until the borrower's credit grade becomes known (*'transitional credit*

'Switching' theories concentrate on what factors motivate an entrepreneur to move to self-employment from wage earning employment. Evans and Jovanovic (1989) were the first contributors to investigate credit constraints in a *'switching'* theory framework. However, they were followed by Cressy (1996c). According to *'switching'* theories, if the initial wealth of an entrepreneur is correlated with his eventual business survival, rationing exists because asset poor entrepreneurs suffer from under investment and hence are more likely to fail.

Finally, theories describing illusory credit rationing, where rationing is based on the entrepreneur's perceptions, show that banks do not under invest but rather over invest in firms. Examples of papers that interpret rationing in this way are the contributions by de Meza and Southey (1996) and Manove and Padilla (1999) and the empirical paper by de Meza (1999). According to these models, banks over-invest rather than under-invest (ration credit to firms) in firms. This is because an entrepreneur's perception of his own ability is highly inflated and therefore his perception of the amount of finance that he needs for his project is not commensurate with his own ability nor with the success likelihood of his project.

Now that I have described the taxonomy of the credit constraints literature, I can give a brief description of the core arguments presented in each group of papers.

<u>*'Transitional'* credit rationing models</u>

I first look at *'transitional'* credit rationing models. The Jaffee and Russell (1976) model from here on referred to as the J-R model, represents the first and best example of a *'transitional'* rationing model. It posits that a bank lends a precautionary amount to a first-time business borrower in order that the bank can, in the intervening period between the first and second period, accumulate behavioural information on the borrower's creditworthiness. It is only when the bank is satisfied with how the borrower has managed to repay his first period balance that it commits to extending a second period loan the magnitude of which is more in line with the borrower's expectations. Hence, supply equates demand only in the second period. The market for loans is in temporary disequilibrium in the first period.

The most salient point about the J-R model, according to Berger and Udell (1995), is that the amount loaned by the bank is a choice variable. In other words, the bank can choose to lend a lower amount to the borrower than requested. This creates excess demand for loans. Since

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rationing'). The common denominator in this synthesis of the two types of credit rationing is that the amount borrowed is increasing in credit constraints.

the demand for finance by the borrower outstrips the supply of finance by the bank, the market is not in equilibrium. However, I have already mentioned that this lack of equilibrium is a temporary phenomenon and confined to the first period of borrowing. After a time, the creditworthiness of the borrower becomes known, as the borrower defaults or fails to default on his repayments. It is assumed that under full information when the bank has collected adequate information about the borrower that equilibrium is restored and the bank has no longer any need for rationing[6].

The model by Jaffee and Russell (J-R) is of particular relevance because their representation of the borrowing situation appears to mirror what happens in reality. This model agrees with circumstantial evidence from bankers who describe first time borrowers as being risky, hence the need to reduce the exposure to them in the first period[7]. The implication of this model is that a bank increases its knowledge of the entrepreneur over time. The model is therefore dynamic to the extent that as knowledge increases, credit constraints can decrease. The model describes the transition from asymmetric information to full-information as the borrower status becomes known. The former case is synonymous with a regime of credit constraints and the latter with a more efficient allocation of credit.

The Petersen and Rajan (1995) model, from here on referred to as the P-R model, exhibits some characteristics of a *'transitional'* rationing model in the sense that it suggests spreading finance over two periods. However, the distinguishing feature of the

P-R model is that it focuses on the affect of relationship and the degree of competition in the loan market on credit availability and interest rates. Not only does it focus on the effects of banking competition on the market for loans, (the Besanko and Thakor (1987b) model also does the same in its separate analysis for a monopolistic and perfectly competitive bank), but it divides lending into two periods, in a way reminiscent of the J-R model. Therefore, investment in a firm is staggered over two periods where investment in each period is conditioned on the outcome of the previous period. It follows that the P-R model is more explicitly a multi-period model than the J-R model[8].

The outcome of the P-R model is that as the bank's market power increases, so also does the probability that lower-quality, higher-risk entrepreneurs will receive finance. Therefore the

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[6] An assumption of the J-R model, as with many other models in the financial literature, is that the bank's supply of funds from deposits is perfectly elastic and that the market for finance is purely competitive.

[7] For example, in data that I obtained from a UK retail bank, all first-period loans, without exception, are assigned a risk level *'high-risk'*.

implication for credit constraints, is that the monopoly power by banks should increase the availability of credit and reduce credit constraints.

This finding also has implications for bank-business relationships. A certain degree of bank market power and indirectly business-bank relationships is viewed favourably by P-R who argue that;

'...credit market competition imposes constraints on the ability of the firm and creditor to intertemporally share surplus. This makes lending relationships less valuable to a firm because it cannot expect to get help when most in need'[9].

Bank-business relationships provide the theme for an important empirical paper by Petersen and Rajan (1994). If bank monopoly power reduces credit constraints and close entrepreneur-bank ties are positively correlated with monopoly power, it follows that businesses cultivating strong relationships should be less likely to be credit constrained. The authors Petersen and Rajan (1994), confirm this hypothesis regarding the positive effect of monopoly power on credit constraints. They find that the main advantage of fostering close ties with a main lender is to increase the availability, rather than the price of lending.

'Equilibrium' credit rationing models

One of the most frequently cited papers in the credit contracting literature, is the path breaking paper by Stiglitz and Weiss (1981), from here on referred to as the S-W model. This follows chronologically on the J-R model described above. This paper belongs to the set of *'equilibrium'* credit rationing papers described earlier.

The basis of the S-W model is that the te

rms of the credit contract (interest rate and collateral) influence the subsequent behaviour of the borrower. If the interest rate or collateral conditions exceed a certain threshold level, higher risk borrowers, (those with greater dispersion of their mean returns from investing in the project), will not be discouraged by the relatively higher cost of capital, while lower risk borrowers will not undertake their projects. What the bank would have gained directly through higher interest rates, it can lose through the indirect consequence of good borrowers dropping out of the borrower group. Eventually, the latter loss can outweigh the former gain to the extent that the bank earns negative returns on a portfolio of borrowers if the interest

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[8] The J-R model does not dwell on the implications of staggering lending over two periods other than to use the two-period format to justify why good borrowers would bide their time until the second period when the bank makes good any shortfall in first period finance.

[9] P.408. Petersen and Rajan (1995)

rate is too high. The outcome of credit constraints is to induce changes in the overall portfolio risk of the pool of borrowers (adverse selection) or induce individual borrowers to undertake higher risk projects in order to recoup their investment (moral hazard).

According to the S-W model therefore, rationing of the type outlined in the J-R model would be counter-productive. I will now explain where this disagreement between the models arises. The J-R model postulates that a bank can allocate sub-optimal funding in the first period of borrowing in order to let the reputation of the borrower develop. However the J-R model does not assume, unlike the S-W model, that this action of the bank raises the probability that the applicants will default. Therefore, the bank inadvertently raises the risk level of its portfolio of first-term business borrowers because it has financed them in a sub-optimal way (Berger and Udell, 1995).

The implication of the S-W model is that *'transitional'* credit rationing, of the kind described by the J-R model, cannot work because it raises the risk profile of the applicants. Therefore, by using the amount loaned as a choice variable as *'transitional credit rationing'* theories suggest, the bank is decreasing the probability of the good project outcome occurring. Rationing the amount borrowed would have counter productive effects.

Bester's (1985) model is another *'equilibrium'* rationing model. It differs most from the three that have gone before in that while the J-R, S-W and P-R models consider interest rates only in the context of credit rationing, Bester's model also considers collateral as an additional risk instrument. In so doing it sets a precedent for including collateral that is also reflected in the paper which succeeds it by Besanko and Thakor (1987b).

Like the S-W, J-R and P-R models, bankers cannot gauge the risk type of the borrower ex ante. In other words, a regime of asymmetric information obtains for the bank/business borrowing relationship.

The main point of Bester's model, is that a bank can create two contracts which are offered to borrowers of both types. High-risk borrowers will select the contract which offers high interest rates in return for low collateral, while low risk borrowers will signal their creditworthiness by accepting the contract comprising high collateral in return for low interest rates. Borrowers will make their risk type known through their choice of contract.

The concept of credit rationing is central to Bester's model, because we shall see later on that no rationing would exist if a bank can set the terms of the loans in such a way that borrowers can self-select themselves. Therefore, high-risk borrowers who have been denied credit and who enter the pool of low-risk borrowers, will not accept the contract offered to all borrowers in this pool. The bank will have tailored the loan terms according to the risk preferences of the low risk borrowers and therefore only the low risk borrowers will accept the loan contract on these terms. The high-risk borrowers have no choice but to accept the high-risk contract, since they are not tempted to accept the contract that the low risk borrowers find acceptable.

Bester's model represents a departure from the other models because it introduces the idea of self-selection. This model has more flexibility than the models presented by S-W and J-R because it assumes that interest rates and collateral can be set simultaneously. The operation of interest rates in conjunction with collateral, allows the bank to supply sets of interest rate and collateral pairings. These mutually exclusive pairings allow the borrowers to self-select into high and low risk pools. Thus high-risk borrowers favour higher interest rates and lower collateral pairings than their low risk counterparts.

Bester points out that as long as borrowers are not constrained by their initial wealth (access to collateral), no credit rationing should take place.

In summarising, the most important contribution of Bester's model is the inclusion of collateral as a risk instrument, and its indication that high and low risk borrowers have mutually exclusive risk preferences allowing them to self-select. Finally, he is the first contributor to acknowledge that wealth constraints could play a role in credit rationing.

We now move on to describe the *'equilibrium'* rationing models of Besanko and Thakor (1987a and 1987b), from here on referred to as the B-T model. Other variations of this basic model are outlined in Boot and Thakor (1994).

The B-T model is very important because it provides the cornerstone for much of the current approach to signalling theories. It leads on directly from Bester's model because, while Bester hinted that binding wealth constraints could cause the process of self-selection to break down, the B-T model directly addresses the issue of binding wealth constraints. B-T argue that binding collateral constraints prevent banks from enticing high and low risk borrowers to self-select into appropriate collateral/interest rate pairings. In this case, rationing credit becomes a useful means of achieving more efficient self-selection, mainly by deterring high-risk borrowers from favouring the collateral/interest rate pairing which the bank intend for low risk borrowers.

Credit rationing is a component of this theory, in so far as it is used to dissuade certain borrowers from applying for a contract they would otherwise find appealing. Credit rationing is therefore used as an additional risk instrument, in addition to collateral and interest rates.

The main outcome of the B-T model, which is relevant to credit rationing, is that under asymmetric information with borrower wealth constraints, low risk borrowers will have their loans rationed. By being rationed, the B-T model implies that low risk borrowers will have their loans given out on a lottery basis. Unlike Bester's (1985) model, described earlier, screening is not fully efficient and therefore credit rationing is an unwanted by-product of efforts to separate high from low risk borrowers.

A model for illusory credit constraints

De Meza and Southey's (1996) model, from here on referred to as the DM-S model, is unlike any of the models that have gone before because it does not deal with credit rationing in the traditional sense. Rather it depicts credit constraints as illusory. It draws on the field of psychology to predict what type of entrepreneur is more likely to successfully obtain credit and how his risk profile compares with the type of entrepreneur who is typically turned down for credit. This model has paved the way for articles such as that by Manove and Padilla (1999).

The unique aspect of the DM-S model that we have not seen in any of the models presented so far, is that an entrepreneur's rather than a bank's actions are instrumental in the decision to allocate credit. So far all models have assumed that the bank unilaterally decides to allocate a certain credit amount (J-R model), set interest rates (S-W model) or set the terms in order that the borrowers self-select (Bester's model and the B-T model). However, no models have focused on the demand side and considered how the entrepreneur can be instrumental in obtaining a loan.

The DM-S model reverses the accepted theory of information. Prior to the appearance of the DM-S model, the concept that the business start-up knows more about his financial prospects than his bank, was regarded as a stylised fact. DM-S argue that the bank rather than the business start-up knows more about the prospects of the business. This is because the bank has the benefit of its collective lending experience and also has a whole portfolio of similar loans with which to extrapolate the risk of the business. As opposed to this, the entrepreneur has only his own individual experience to draw on and at the start-up stage this body of experience is negligible. Not only this, but DM-S argue that only the least conservative of individuals choose to become entrepreneurs. The implication of this argument is that entrepreneurs are, by definition, high-risk individuals who are drawn into business by the prospects of high returns. Because entrepreneurs are over-confident about their success probability, their estimate of their own success probability is biased. Therefore, only the bank has an objective and comparatively accurate measure of the expected return on a business project.

The DM-S model argues that credit rationing is a relative concept. What entrepreneurs perceive as credit rationing, is only the bank's legitimate response to their high-risk.

The conclusion of the DM-S model is that the optimism model explains the unwillingness of entrepreneurs to take out bank loans, better than the conventional moral hazard or adverse selection models.

The way an optimism model explains the situation is as follows. Because a bank cannot ascertain the individual borrower's creditworthiness, although it knows the default rate of the population of borrowers, the bank formulates interest rates, collateral amounts and loan amounts in such a way as to compensate itself for its uncertainty i.e. it pools the terms that it offers to the low and high-risk borrowers. Due to the buoyant spirits of would-be entrepreneurs, their over-confidence in their own ability and in their expected project returns, ensures that the demand for loans exceeds the supply of loans. DM-S argue that the average project could be a loss maker. This ensures that able pessimists are crowded out of the market for finance since they would regard the terms offered by the bank as 'actuarially unfair for their own characteristics'[10]. While standard models conclude that the bank lends too little, the optimism model concludes that the bank is justified in the magnitude of its lending. The authors argue that banks are entirely justified for being conservative in the amount they lend to start-ups because their evaluation of projects and risk is more realistic in general than the evaluation of the projects by many of the entrepreneurs themselves[11].

'Switching' models of rationing

The Evans and Jovanovic (1989), from here on referred to as the E-J model, represents the first *'switching'* model that shows the factors motivating entrepreneurs to switch from wage to self-employment. In so doing, it sheds light on whether the entrepreneur is rationed or not.

The core argument of the E-J model is that if a lower collateral/loan amount ratio were introduced by the bank or if the entrepreneur had higher initial wealth, if credit rationing exists, then these two phenomena would induce more entrepreneurs to switch from waged to self employment.

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[10] P. 385. 'The borrower's curse; optimism, finance and entrepreneurship'.

[11] Unfortunately, the DM-S model does not define the proportion of the entrepreneurial population that it characterised by optimism but they set it at 50 percent in the model.

An additional argument of the E-J model is that if better quality entrepreneurs demand more capital at a given level of assets and banks lend in proportion to assets, then better quality entrepreneurs will perceive themselves to be more credit constrained than lower quality entrepreneurs. The more able entrepreneurs will find that their expected profits are lower than they would hope for if they are given the same level of finance as less able entrepreneurs. They do not find that the profits they expect to earn from self-employment adequately compensate them for, i.e. are equal to the opportunity cost of switching from wage-employment.

The main assumption of the E-J model is that entrepreneurs with higher skills levels expect to receive comparatively more finance than their lower skilled counterparts in order to cover their higher opportunity cost of making the switch to self-employment.

This argument of the E-J model that higher quality entrepreneurs perceive themselves to be more constrained vis a viz. their lower quality counterparts, directly contradicts the conclusion of the D-MS model that lower quality entrepreneurs feel themselves to be more constrained[12].

An advantage of the E-J model compared to other models, is that it is relatively easy to test for the presence of credit constraints using its framework. The hypothesis that empiricists testing for the existence of credit constraints should test, is whether there is a correlation between assets and the level of start-ups. If an entrepreneur can borrow all he wants for a fully capitalised business, there will be no relationship between assets and start-ups because entrepreneurs are not limited by the initial wealth i.e. irrespective of the level of their start-up assets, high quality entrepreneurs receive adequate funding for their project.

There is a further test for the existence of credit constraints using the E-J model criteria that was carried out by Cressy (1996c). Assets should be positively correlated with survival if start-ups are credit rationed. The rationale for this test is based on the predicted correlation between assets and the likelihood of obtaining the optimal level of finance requested, if credit rationing operates. The corollary to this is that under-funded, higher quality firms are less likely to survive if a bank fails to supply them with the amount of finance they need to realise their business project[13].

[12] You will recall the arguments of the DM-S model presented above that more confident, higher-risk entrepreneurs request higher levels of finance than less their pessimistic, lower-risk counterparts.
[13] Cressy (1996) found that higher quality firms, in terms of human capital, were more likely to survive and that these high quality firms were also more likely to receive finance. The bank could therefore 'pick winners'. Therefore, Cressy concludes that E-J rationing does not exist because a bank is able to differentiate between high and low quality firms. Where human capital variables enter his regressions,

2.4 The mathematical context of the credit constraints models

The sections below provide the mathematical detail of the models presented in the previous section.

2.41 The Jaffee and Russell (1976) model

Jaffee and Russell describe all borrowers as being either 'honest' or 'dishonest'. The bank cannot differentiate between the two categories ex ante.

The J-R model describes two periods. A loan, L, is taken out in the first period to supplement first period consumption C_1. Income, Y, is generated both in the first period, Y_1, as well as the second period Y_2. Consumption in the second period, C_2, is reduced by the amount of the loan repayment. This loan repayment amounts to the loan principle L multiplied by the interest rate factor R representing $(1 + r)$ where r is the interest rate.

$$C_1 = L + Y_1 \qquad \textbf{41.1}$$

$$C_2 = Y_2 - LR \qquad \textbf{41.2}$$

Where C_1, C_2 = first period and second period consumption

L = the amount of the loan

Y_1, Y_2 = first and second period income

The entrepreneur aims to maximise utility. Utility, in turn, depends positively on consumption in the first and second period. Therefore total utility, U, is a function of consumption over both periods, C_1 and C_2, and can be expressed as $U = U(C_1, C_2)$. Utility should also always be positive. Intuitively, we know that individuals prefer higher to lower and positive to negative utility. Therefore, the J-R model also postulates that utility in both periods is positive with respect to consumption in both periods;

$$dU / dC_1 > 0, \; dU / dC_2 > 0 \qquad \textbf{41.3}$$

Maximising utility $U[L + Y_1, Y_2 - LR]$ with respect to L gives;

$$\frac{dU}{dL} = U_1 - U_2R = 0 \qquad \textbf{41.4}$$

leading to a loan demand function of the form

$$L^* = L^*[R] \qquad \textbf{41.5}$$

Assuming that dL^*/dR is negative, the J-R model shows that higher values of L, (higher loans), are associated with lower values of R (cost per unit of servicing the loan is lower).

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they cancel out any relationship between asset levels and survival. High quality firms are more likely to survive and they are also more likely to have higher levels of initial wealth.

If default occurs, the penalty arising from default, measured by a constant Z, is subtracted from income in the second period Y_2. The penalty of default is the reduction in the earnings capabilities of entrepreneurs as their lack of creditworthiness becoming known. It is assumed that the penalty arises in the third period, although this is not explicitly stated. Default is only disadvantageous for the borrower (lowers borrower utility), if the cost of default, (forfeiture of future lending and loss of reputation), is higher than the value of loan repayments outstanding. If the cost to the borrower of repaying the loan is lower than the benefit to be gained from defaulting, a rational dishonest borrower will pay what it owes to the bank.

Dishonest borrowers therefore, make a decision as to whether they can increase their utility by defaulting or not. This decision is influenced by the size of the loan, where larger loans increase the temptation to default because they increase the borrower's utility from defaulting. A borrower adopting an honest strategy has consumption in the first and second period of;

$C_1 = Y_1 + L^*$ ***41.6***

$C_2 = Y_2 - L^*R$ ***41.7***

By following a dishonest strategy consumption in both periods is expressed as;

$C_1 = Y_1 + L^*$ ***41.8***

$C_2 = Y_2 - Z$ ***41.9***

where Z denotes the penalty arising from default. The two courses of action only differ in the level of consumption for the second period C_2, and dishonest entrepreneurs default when $Z < L^*R$. In other words, dishonest entrepreneurs default when the penalty of default is less than the value of the loan repayments.

The J-R model postulates that honest borrowers would prefer a first period contract which extends them less credit than they demand, in return for these long term gains. The model can be explained graphically as in **Figure 2.1**. In **Figure 2.1** the x-axis is labelled L to represent the magnitude of borrowing undertaken by the firms and the y-axis labelled R, to denote the corresponding interest rate factor. I denotes the level of the interest rate factor below which it is uneconomical for the bank to lend. The bank has to cover its own cost of borrowing. The indifference curves, I and II, (not to be confused with U_I and U_{II}, representing first and second period utility discussed above), show an ordering of utilities where the utility over the curve I is less than the utility over the curve II.

The point S represents the intersection of the supply schedule and the demand schedule for loans. However, the equilibrium point E lies on a higher utility curve, despite rationing occurring at this point (quantity demanded exceeds quantity supplied at this point as the demand curve lies to the right of *E*). According to Jaffee and Russell, the reason an honest borrower would prefer to be rationed is as follows;

'*Borrowers who are honest at contract S prefer the equilibrium with rationing at contract E. The advantage of rationing is that fewer individuals default at the smaller loan size, and under competition these gains are passed on to the honest bor*rowers'[14].

The most important conclusion of the J-R model is that honest borrowers prefer to receive less borrowing than they demand from the bank i.e. have the amount they requested on their loan rationed, in return for a lower interest rate and some future payoff. This future payoff arises because fewer borrowers will default on their loan if they have to repay less. Under perfect competition the bank will pass on these future gains to the borrowers.

2.42 The Stiglitz and Weiss (1981) model

We have already seen that according to the J-R model, lending by the bank is staggered over two periods. In the first period, the borrowers are sub-optimally financed and only in the second period does the bank make good the shortfall. This theory is directly contrary to the predictions of the Stiglitz (S-W) paper that I will discuss in this section.

The S-W paper has many dimensions. However, the one of most relevance to my current analysis is the section dealing with credit rationing.

S-W assume that there is a mix of high and low risk projects in the population of borrowers, all of which yield the same average return. However, the low risk borrowers have a lower spread around their mean return.

Risk is denoted by θ, where a higher value for θ denotes a higher risk. If an entrepreneur cannot repay the full amount of borrowing plus interest, *L (1 + r hat)* from the returns, *Y*, on his project, he stands to lose the value of his collateral *C* and any returns he has made. The net return to the entrepreneur π, is a function of the interest rate *r hat* and the returns *Y* he makes from his project, where *r hat* denotes the interest rate charged to an individual borrower.

The net return to the entrepreneur can be expressed in terms of two scenarios. In the first scenario the entrepreneur earns a sufficiently high return, *Y*, to cover the cost of servicing his debt. In the second scenario, he forfeits his collateral, *C*, because he has not generated a sufficiently high return. The net return to the entrepreneur, π, can be written as;

[14] P.661. Jaffee and Russell, 1976. 'Imperfect information, uncertainty and credit rationing'.

$$\pi(Y, \hat{r}) = max(Y - (1 + \hat{r})L, \ -C) \qquad \textbf{42.1}$$

The net return to the bank, ρ, is modelled likewise by two scenarios. Either the entrepreneur does not generate enough funds on his project to repay his loan. In this case, the bank takes the proceeds from the project, *Y*, and it also seizes any collateral, *C*, that the entrepreneur commits to the bank. Alternatively, if the entrepreneur does not default on his loan and hence earns enough of an income to repay his loan, the bank earns its normal return on the money it loaned to the business in which case it gets *L (1+ r hat).*

$$\rho(Y, \hat{r}) = min(Y + C, \ L(1+ \hat{r})) \qquad \textbf{42.2}$$

S-W argue that net bank profits, ρ, increase to a certain threshold interest rate level, r_1, but that after this threshold is reached, the low risk borrowers drop out. Successive increases in the interest rate, *r hat,* after r_1, increase net bank profits ρ. This increase in ρ continues until the positive effect of the interest rate hike, is neutralised by rising default levels, where default rises as a result of increases in the level of risk associated with projects remaining in the portfolio.

Figure 2.2 illustrates this relationship between interest levels and the level of profits earned by the bank. In **Figure 2.2** net profits to the bank, ρ, are associated with changes in the interest rate, *r hat*. The returns curve is like a jagged line with two discontinuities. The first discontinuity occurs at r_1 up to which both high and low risk firms apply for credit. The returns curve plunges on interest rates reaching r_1, where the low risk firms drop out. The curve rises more gradually after r_1 before plunging again at r_2, when returns become zero as rising default rates cancel out any returns that the bank generates from higher interest rates.

The S-W model deals directly with the issue of credit rationing. Their chain of reasoning is as follows. Because adverse selection happens if the bank charges the equilibrium, (market clearing), interest rate where only high-risk firms are left in the bank's portfolio, it makes sense for the bank to charge an interest rate below the equilibrium interest rate. At this non-market clearing interest rate, the demand for loans exceeds the supply of loans. However, the bank is not prepared to raise the interest rate in order to clear the market. It earns higher profits at this non-market clearing interest rate, simply because the low risk firms have remained in the bank's portfolio. The low risk firms would be driven away if the bank raised this non-market clearing interest rate. The result of raising the interest rate would be that the bank's portfolio would contain a more homogeneous set of high-risk firms and low risk firms would be deterred from applying. This comparatively high proportion of high-risk firms in the bank's portfolio relative to low risk firms at the equilibrium interest rate, would undermine the bank's profits. The bank therefore chooses to charge a lower interest rate and allocate credit on a randomised basis (if it cannot differentiate between the high and low risk firms a priori).

It is worth mentioning here that S-W do not advocate the type of credit rationing, i.e. staggered financing, proposed by J-R because they maintain that projects are *'not divisible'*[15]. The expression *'not-divisible'*, implies that if the entrepreneur does not get the level of funding that he requests, that the project will not be undertaken at all. In other words, partial financing of projects of the kind suggested by J-R cannot exist, according to the assumptions of the S-W model.

Figure 2.3 shows the non-monotonic relationship between the interest rate that is charged to borrowers and the expected return to the bank per £1 loaned, ρ *bar.* The interest rate, *r hat*, is related to loan amount supplied, L_S, and simultaneously, in the bottom half of the graph, to net bank returns, ρ *bar.* In the top half of the graph, it is seen that the supply of loans L_S increases and then decreases, due to the adverse selection effects described earlier. As the interest rate rises, lower risk firms drop out of the portfolio, causing reductions in overall bank profits. The bank's supply function peaks at r^* because at interest rates above r^*, diminishing returns to profits ρ *bar* set in. Accordingly, the maximum point on the supply schedule corresponds to an interest rate of r^* and the maximum level of net profits. After the amount of finance, L_S, that the bank in prepared to supply peaks at the interest rate of r^*, the function becomes negative. The supply schedule L_S becomes negative after this point as the bank is forced to impose tougher rationing procedures in order to deter high-risk borrowers from applying at these higher interest rates.

There is excess demand at r^* (L_D exceeds L_S) and the market is not cleared. However, the bank is quite happy to charge the non-market clearing interest rate, r^*, where its net profits, ρ *bar,* are maximised. On the other hand, if the equilibrium rate of interest r_m were charged (L_D equals L_S), the bank's return ρ *bar* would not be maximised.

According to the S-W model, it makes sense for a bank to ration credit by denying some borrowers finance under perfect information. Under imperfect information, the characteristics of low and high-risk borrowers appear the same to the bank. Therefore the bank cannot introduce effective screening procedures in order to differentiate between high and low risk borrowers.

Now that the S-W model has been described, I now turn to the main implications of the model and compare it with the J-R model described earlier.

According to Stiglitz and Weiss, if the bank decides to lend less funds than a firm needs for its project to succeed, the bank causes its portfolio to become riskier. Under-capitalised firms have a higher likelihood of failing than firms that have been sufficiently capitalised. This is why they reason that it is better to decline some projects and optimally finance the remainder, rather than ration the amount of individual loans. The S-W model therefore disagrees with the J-R model in this respect.

'If projects either succeed or fail, and yield a zero return when they fail, then the increase in the collateral requirement of loans will increase the riskiness of those loans'[16].

A similar situation would arise if potential borrowers had different *ab initio* asset or wealth levels. Borrowers with higher asset levels would not be as discouraged by the heightened collateral requirements, as borrowers with lower asset levels. These borrowers might be less risk adverse than borrowers who had fewer assets. In other words, the incentive effects brought about by higher collateral requirements would be commensurate with the level of initial wealth, *W*, of the firms. Those wealthier firms might be less risk adverse than businesses having fewer assets. The bank rather than decreasing the risk of its portfolio, would inadvertently increase the risk on its portfolio through the adverse selection of borrowers[17].

2.43 The Bester (1985) model

Bester presents two scenarios. In the first scenario the cost of providing collateral is zero. In the second scenario the cost of providing collateral is greater than zero.

Bester's assumptions are similar to those of Stiglitz and Weiss (1981). The expected returns of the riskier borrower b are the same as those of the less risky borrower a, where Y_a denotes the income of a low risk borrower and Y_b denotes the income of a high-risk borrower.

$$E\{Y_a\} = E\{Y_b\} \qquad \textbf{43.1}$$

The expected value of the income generated by high-risk borrowers, $E\{Y_b\}$, is the same as the expected value of the income generated by low risk borrowers, $E\{Y_a\}$. However, not only is the income of the high-risk borrower, Y_b, more uncertain by definition (greater dispersion around the expected value) but overall, high-risk projects yield a higher return on investment. This higher overall yield of the high-risk project would be seen if the equality **43.1** above were integrated. The difference between the high and low-risk project would still

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[15] P.396. 'Credit rationing in markets with imperfect information'.

[16] P.402 Stiglitz and Weiss (1981)

have a positive value. In other words, imagine two distributions representing high- and low-risk borrowers. The area under the curve describing the distribution of returns $F_i\ (Y)$ (integrating the returns function) for the risky borrower, $F_b\ (\ Y)$, is greater than the area under the returns curve for the less risky borrower, $F_a\ (\ Y\ )$.

$$\int_0^y [F_b(\ Y) - F_a(\ Y\ )]\ dY \geq 0 \qquad \textbf{43.2}$$

Entrepreneurs are compelled to borrow from a bank because their initial wealth endowment W is not sufficient to finance their investment I. Therefore, $W < I$. They finance their project by borrowing the amount $L = I - W$.

As described in **section 2.2**, the loan contract is described by an interest rate r. Bester's model also includes collateral, C, in his model framework. As in the S-W model, bankruptcy occurs if the returns to the business R and the value of the collateral C are not sufficient to cover the cost of servicing the debt. In other words, bankruptcy occurs when $C + Y < (1 + r)\ L$.

The expected profits to the entrepreneur by undertaking a credit contract π are similar to those in the S-W model. The only difference between the two models at this stage is that Bester assumes that there may be a cost to the firm of using collateral. This cost is assumed to be proportional to the amount of collateral by a constant k.

The expected profits to the entrepreneur of taking up a loan contract π are;

$$E\ (\pi)^F = E\ \{max[\ Y - (1 + r)\ L - kC,\ \ - (1 + k)C\ ]\ \} \qquad \textbf{43.3}$$

where in the first instance he manages to generate sufficient returns to repay his borrowing and the interest on his borrowing in addition to the cost of using collateral kC. In the second instance, he loses his collateral and incurs the cost of using it $(1+k)\ C$.

On the other hand, the bank receives its expected rate of return consisting of $(1 + r)\ L$ if the business generates a return. Alternatively, the bank receives $Y + C$, indicating the repossession of collateral and the retention of any returns, Y, generated by the business, if the business is unable to repay its borrowing. The expected returns to the bank are written as follows;

$$E\ (\pi)^B = E\ \{min[\ (1 + r)\ L,\ Y + C]\} \qquad \textbf{43.4}$$

The main cornerstone of the Bester paper, is that the bank can devise a set of contracts such that high and low risk borrowers will prefer one risk instrument (collateral or interest rates) over the other. The marginal rate of substitution between collateral and the interest rate for one group of borrowers will be different from the marginal rate of substitution for the other

[17] Wette (1983) went on to prove that adverse selection does indeed take place if the bank increases its

group. Therefore the two groups will choose contracts with different combinations of collateral and interest rate. Bester defines a pair of loan contracts (π_α, π_β) as being incentive compatible if;

$E_a(\pi_\alpha) \geq E_b(\pi_\beta); E_b(\pi_\beta) \geq E_b(\pi_\alpha)$ **43.5**

In other words, the expected profits accruing to borrower *a*, E_a, from undertaking contract π_α are greater than the profits it would expect from undertaking contract E_β and vice versa. The bank then has to devise two sets of mutually exclusive contracts, allowing it to establish the risk type of the business by its choice of contract. Through self-selection by entrepreneurs for a particular contract, they reveal their risk category.

Figure 2.4 shows why these two types of entrepreneur exhibit different collateral/interest rate preferences. These collateral/interest rate preferences are described by two different boundary areas *aa'* and *bb'* for each borrower type for all projects offering positive net profits. These boundary areas show where the two different types of collateral/interest pairing contracts are located. In *area II* collateral, *C*, is less than the repayments on the project $(1 + r)L$. There is an incentive for risk-takers in *area II* to gamble on high-risk projects because the collateral they would forfeit is less than the repayments they would avoid by defaulting. Low-risk investors of type *a* will drop out of the market in *area II*. In area *I*, all low-risk *a* investors demand a loan.

In agreement with the predictions of the S-W model, raising the interest rate is only going to cause the mix of borrowers to become more risky, as type *a* borrowers drop out. In *area II* only type *b* borrowers apply for finance. Adverse selection of the type described by S-W occurs in *area II*. Since *b* borrowers yield lower expected net profits to the bank, a situation where all *b* type borrowers were to apply for finance would be unacceptable to the bank. There would be no adverse selection if a bank offered contracts only along the $C = (1 + r)L$ schedule. Along this line interest rate hikes are always accompanied by a simultaneous rise in collateral requirements in such a way that the bank is covered against borrower default because the value of the collateral taken is equal to the value of the loan plus interest payments.

This is where Bester refers to credit rationing. He argues that an entrepreneur's project is worth undertaking, from the entrepreneur's perspective, if the projects generates a high enough expected return, $E_i(\pi)$, to cover the opportunity cost of using those assets *W* (which he could offer as collateral on a loan). The opportunity cost of using his wealth W is

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collateral requirements.

interpreted as the return he could earn by liquidating them and depositing them at the safe rate of interest $i*$. Bester argues that;

'Credit rationing is said to occur if some entrepreneur i faces a positive probability of being rejected at each contract π_j* which maximises his expected profits and at the same time $E_i(\pi) > (1 + i*)W$[18]'.

In other words, if there is a positive expected return for the project over and above the opportunity cost of the project, $(1 + i*)W$, and still the entrepreneur is turned down, then he is credit rationed. If collateral is costless and the entrepreneur had limitless collateral, then the bank could extend the entrepreneur a loan along the line $C = (1 +)L$. With costless collateral all projects would be fully funded and undertaken. They would lie along the line where collateral equalled the full loan value. However where $C < (1 + r)L$, the bank would ration credit and therefore an entrepreneur would face a non-zero probability of having his loan application turned down.

A further conclusion from Bester's model, that reflects the S-W concept of adverse selection, is that high-risk *area II* entrepreneurs are self-selecting. They are less averse to higher interest rates because the returns on their projects are higher. It is still worthwhile for them to undertake their projects even at high interest rates. This is because their projects exhibit a positive net present value even at high interest rates and exceed the opportunity cost of undertaking the project. On the other hand, low risk entrepreneurs are less insensitive towards high interest rates and prefer the low interest rate/ high collateral contract. This is because they are not so deterred by the prospect of forfeiting their collateral (they are more certain about the security of their investment and the probability of generating the return) but high interest rates would greatly undermine the net present value of their projects.

The conclusion of Bester's model is that a bank can perfectly distinguish between high and low risk borrowers using collateral and interest rate pairings. A bank could ration credit to high-risk borrowers, if it chose to do so, since these borrowers would automatically prefer high interest rates in lieu of increased collateral requirements. It would be possible to perfectly separate the high-risk from low risk borrowers based on their different marginal substitution rates of collateral for interest rates (indifference curves) at this pooling equilibrium.

[18] P.852 Bester, 1985

2.44 The Besanko and Thakor (1987b) model

The Besanko and Thakor (1987b) models describe two scenarios. In the first scenario, the bank is a price setting monopolist. In the second scenario, which is perhaps more realistic, the bank is operating in a perfectly competitive market.

The key feature distinguishing this model from others, is the assumption it makes about the returns R made by entrepreneurs on their loans. R is not a choice variable but a fixed constant. This means, that a borrower does not choose to be a high or low risk borrower depending on the interest rate regime or collateral requirements. What makes him high-risk, is his lower probability of attaining the given returns R on a project. His likelihood of getting a return R on his borrowing is P. Lower risk entrepreneurs have higher likelihoods P_1 of achieving a return of R. This is written as;

$$0 < P_2 < P_1 < 1 \qquad \textbf{44.}\textit{1}$$

where P_2 is the probability of the higher risk borrower obtaining a return R on his borrowing and P_1 the corresponding probability for a low risk borrower.

Asymmetric information prevails in the market for credit because a borrower knows his likelihood of obtaining a return R, while the bank cannot distinguish between borrowers with different success probabilities. All the bank knows is that a fraction γ of all entrepreneurs are high-risk types $(P = P_2)$ and that the remainder $(1- \gamma)$ are low risk types $(P = P_1)$. In other words, the bank knows from past lending experience the proportion of borrowers in its portfolio that turn out to be bad and the proportion that turn out to be creditworthy. It just cannot distinguish between individuals ex ante. The B-T model therefore is similar to the J-R, S-W and Bester models in its interpretation of asymmetric information.

The other two constants apart from R are the initial wealth, W, of the entrepreneur (which can be used as collateral C) and b, the percentage payoff if the entrepreneur deposits his capital in non-risky, interest bearing assets e.g. bonds. b (a rate) is, therefore, the opportunity cost to the entrepreneur of going into business and undertaking a comparatively risky project.

The B-T model begins by making predictions for a monopolistic bank. The main prediction is that <u>*no collateral is requested from the borrower*</u>. Since a monopolist takes all the surplus or excess profits accruing to the borrower, and since collateral is not an efficient way of claiming all these excess profits, collateral is not used as a way of screening borrowers under monopoly. Therefore, no collateral is used in the credit contract.

To see how the B-T model comes to this conclusion, consider a credit contract as a set of three variables that the bank can change to attract entrepreneurs of certain risk types and discourage others. The bank can change the interest rate factor $(1 + r)$ on the loan which is assumed to be £1. The bank can also change the collateral level C, and finally, it can change its probability of granting credit π. Therefore, for entrepreneurs of risk type P_1 and P_2, the bank must choose the optimal $\{ (1 + r_i), C_i \ , \pi_i \}$ for $i \in \{ 1, 2 \}$. The bank must formulate the credit contract in such a way that the borrower will reveal or tell the truth about his default probability. Secondly, the bank must choose a contract that yields the bank non-zero profit levels.

In order to offer the two contracts to the two types of entrepreneurs in such a way that entrepreneurs of one risk type do not covet the contract offered to the other risk type, the contracts have to be carefully structured. In this way, the low risk types will prefer the low risk contract and the high-risk types will prefer the high-risk contract. This self-selecting mechanism described by the B-T model also operates in the Bester model.

This self-selecting mechanism works in the following way. The probability of granting credit π_1 to a lower risk borrower $(P = P_1)$ is higher than the probability of granting credit π_2 to a higher risk borrower $(P = P_2)$. In the equations below, the terms extended to a lower risk borrower $(1 + r_1)$, C_1 and π_1 are all tailored in such a way as to ensure that lower risk borrowers will choose this contract. Then, the situation is reversed for the contract offered to the higher risk borrower. The likelihood of granting credit π_2 to a higher risk borrower $(P= P_2)$ is higher and the terms of the contract $(1 + r_2)$, C_2 and π_2 induce higher risk borrowers to choose this contract.

The decision an entrepreneur has to make when going into business is whether or not to invest his initial wealth, W, in non-risky, interest bearing assets allowing him to earn $W + b$. Alternatively he can use his wealth W as collateral, C, on a loan of £1 earning him a return with probability P_1 for lower risk borrowers and P_2 for higher risk borrowers. The borrower is assumed to know his return likelihood but the bank does not. The decision faced by the entrepreneur when setting up business is described in the equations below. This is expressed as entrepreneur's likelihood π_i of receiving a loan multiplied by the expected yield on the project (the return minus the cost of the capital $P_i \, [R - (1 + r_i)]$. The interest rate the entrepreneur would have earned on bonds b is subtracted from his project as is the expected loss to the entrepreneur if he defaults $[1 - P_i] \, C_i$.

$$\pi_1 \{ P_1 [R - (1 + r_1)] - [1 - P_1] C_1 - b \} \geq \pi_2 \{ P_1 [R - (1 + r_2)] - [1 - P_1] C_2 - b \} \quad \textbf{44.2}$$

$$\pi_2 \{ P_2 [R - (1 + r_2)] - [1 - P_2] C_2 - b \} \geq \pi_1 \{ P_2 [R - (1 + r_1)] - [1 - P_2] C_1 - b \} \quad \textbf{44.3}$$

The <u>*prediction of the B-T model for a monopolistic bank is that no collateral is supplied by the borrower or required by the bank*</u>. In other words, $C = 0$. This outcome holds true both for the situation where there is full information of the borrower's risk status and under asymmetric information.

The reason B-T can justify this conclusion, is that collateral is an inefficient way of providing the monopolistic bank with a tool for fully claiming all the excess profits earned by the borrower. By keeping interest rates higher for the low risk borrower, the monopolist is assured that he can extract all of the excess profits earned by the low risk borrower (in the absence of asymmetric information). If collateral were used, the low risk borrower would be tempted to offer more collateral in exchange for a reduction in the interest rate since he knows he has a low likelihood of default and it will be therefore not likely that he will forfeit his collateral. The monopolist does not want this situation to arise because he wants to claim all the excess profits earned on the project via the higher interest rate.

In reality, these model predictions for monopoly appear unrealistic. In practice, collateral is taken on borrower projects and the prediction that a bank does not use collateral seems difficult to reconcile with the empirical evidence that banks use collateral (Berger and Udell, 1993). Therefore, perhaps the predictions of the B-T model for perfectly competitive lending markets may be more in tandem with banking practice. Since entrepreneurs do have a choice of banks, the monopolistic model is possibly unrealistic.

We therefore turn to the B-T model, as applied to the case of a perfectly competitive market for finance. Similar to the reasoning behind the monopolistic market outlined above, banks will maximise their net profits

$$Max\ \gamma\, \pi_1\{P_1\,[R-(1+r_1)\,]-[1-P_1]\,C_1-b\}+$$
$$(1-\gamma)\,\pi_2\{\delta_2\,[R-(1+r_2)\,]-[1-P_2]\,C_2-b\} \qquad \textbf{44.4}$$

where γ is the fraction of borrowers he bank has known in the past to be low risk and $(1-\gamma)$ the fraction of borrowers the bank knows have been high risk. π_1 and π_2 are the acceptance probabilities of borrowers for the low- and high-risk contracts respectively.

Unlike the case of a monopoly market were the monopolist bank extracts all the excess profits of the borrower, the assumption under a competitive market for finance is that the bank makes profit levels equal to its deposit rate r_D. In other words, a zero profit condition applies.

$$P_i(1+r_i)+\ [1-P_i]\,C_i=r_D \qquad i\in\{1,2\} \qquad \textbf{44.5}$$

Finally, the B-T model looks at two initial wealth W scenarios. I choose to describe the scenario where the level of collateral, C, is constrained by the wealth of the entrepreneur, because this is what most likely reflects reality. Entrepreneurs, particularly the owners of start-ups and small SMEs, are not likely to have large amounts of free, collateralisable assets to offer a bank. It seems therefore reasonable to confine the discussion to the case where there are wealth constraints. In any case, the level of collateral demanded C cannot exceed the wealth W of the entrepreneur;

$$0 \leq C_i \leq W, \qquad i \in \{1, 2\} \qquad \textbf{44.6}$$

According to the B-T model, under asymmetric information with binding wealth W constraints, <u>*all high-risk borrowers will obtain a loan but low risk borrowers will have their credits randomly allocated*</u>. The latter condition of randomly giving out credit to low risk borrowers is necessary in order to discourage high-risk borrowers who are paying higher interest rates, from coveting the contract offered to lower risk borrowers.

This conclusion is very similar to that obtained by Bester (1985), whereby high-risk borrowers do not provide collateral and are charged higher interest rates than lower risk borrowers. Additionally, lower risk borrowers are charged collateral. Unlike Bester (1985) however, the B-T model predicts that there is rationing in equilibrium even with collateral, because there are limits to which a low risk borrower can signal his creditworthiness using collateral (binding wealth constraints apply).

The predictions of the B-T model are threefold and relate to the equilibrium interest rate α_i, collateral level, C_i, and finally the likelihood of being offered a loan π_i. The predictions for each borrower type P_1 and P_2 are as follows. The low risk contract carries a lower interest rate than the high-risk contract. The lower risk contract implies that borrowers post all their wealth as collateral. Finally, the low risk contract carries a positive likelihood that borrowers are turned down because the acceptance probability is less than one.

$$(1 + r_2) = r_D / P_2, \qquad (1 + r_1) = [r_D - (1 - P_2)\, W] / P_2 \qquad \textbf{44.7}$$

where r_D is the interest rate on bonds, $(1 + r_2)$ the interest factor charged a high-risk borrower and $(1 + r_1)$ the interest factor charged a low-risk borrower.

$$C_2 = 0 \qquad C_1 = W$$

where C_2 is the collateral charged a high risk borrower and C_1 the collateral charged a low risk borrower;

$$\pi_2 = 1$$

$$\pi_1 = [P_2\,(R - (1 + r_2) - b] / [P_2(R - (1 + r_1)) - (1 - P_2)W - b] \qquad \textbf{44.8}$$

where π_2 is the proportion of high-risk loans that are accepted and π_1 is the proportion of low risk loans that are accepted.

It is important to note that the bank would prefer if low risk borrowers were not rationed. The only reason they are rationed is that the bank cannot ascertain their risk status ex ante. As Besanko and Thakor note;

'If the bank can perfectly sort borrowers into distinct risk classes based on observable differences alone, then there would not be any rationing'[19].

In reality, what most likely happens is that banks sort borrowers into coarsely classified groups based on their observable characteristics in order to reduce the influence of asymmetric information. The coarsely classified groups contain borrowers of roughly similar characteristics. In other words, there would be greater within-group or intra-group homogeneity, than if the borrowers had not been coarsely classified. This minimises the effect of credit rationing to good borrowers.

2.45 The De Meza and Southey (1996) model

The de Meza and Southey (DM-S) model differentiates itself from others that have gone before because of its assumption that the entrepreneur's perception of his project returns are biased and therefore only the bank can objectively evaluate a project's risk.

The expected income earned by a project Y_E are a function of the perceived probability of the project's success P_P, its actual success probability, P, and the entrepreneur's perceived income if the project is successful Y_P. The actual success probability of the project is known to the bank alone as a consequence of *'long experience and with the benefit of detachment'*[20]. Therefore, the expected income earned by a project is as follows;

$$Y_E = P_P * P * Y_P. \qquad \textbf{45.}\mathit{1}$$

Y_P can in turn be rewritten as a perceived rate of return $(1 + r_P)$ on the capital employed, K, in the project. The DM-S model postulates that if only half of the population of entrepreneurs comprises optimists, in equilibrium only optimists are active and the more able pessimists will have dropped out of the applicant pool. The model set out to prove this as follows. DM-S assume that there is not an opportunity cost to entrepreneurship and therefore no safe rate of return unlike the safe rate of return, b, seen in the B-T model. All entrepreneurs set out to maximise their expected return but their expected return is biased by their perception of the success probability, P_P, and internal rate of return $(1 + r_P)$ of the project.

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[19] P.678 Besanko and Thakor (1987a)

[20] P.378. The borrower's curse: optimism, finance and entrepreneurship'.de Meza and Southey.

The loan, L, taken out by the business should cover the shortfall in the amount of capital, K, needed to fund the project after the entrepreneur has invested a portion of his wealth, W, equivalent to S in the project. Put another way, $L = K - S$.

The break even condition for the bank is that the probability of receiving the full amount of the loan, L_G, (arising if the project is successful) when added to the probability of receiving nothing is the project fails, L_B, equals the breakeven loan size, L. This is expressed as follows;

$PL_G + (1 - P)L_B = L$ **45.2**

From the entrepreneur's point of view, the expected wealth from a project, W_E, equals the perceived income to the entrepreneur following the success of the project, minus his loss if the project is unsuccessful plus whatever wealth he has left over after investing in the project.

$W_E = P_P P (Y_P - L_G) - (1 - P_P)L_B - (W - S)$ **45.3**

where P_P is the subjective probability of the project succeeding, Y_P the subjective expected income generated by the project, L_G the amount to be repaid to the bank if the project succeeds, L_B the amount to be repaid if the project fails and $(W - S)$ the amount of initial wealth remaining to the entrepreneur after he has invested an amount, S, in the project. In order to find the equilibrium level of expected project wealth, DM-S substitute **45.2** into **45.3** (they also leave out the constants $(W - S)$ in the subsequent equations).

The expected wealth, W_E, from the project now becomes;

$W_E = P_P P (Y_P - L_G) - (1 - P_P)[(L - P L_G)/(1 - P)]$ **45.4**

Differentiating expected wealth with respect to the repayments to the bank in the successful state gives the following;

$\delta W_E / \delta L_G = [P(1 - P_P)] / (1 - P) < 0$ **45.5**

An optimist will have a perceived probability of his project succeeding above unity with $P_P > 1$ because he is unrealistically upwardly biased. Therefore, if optimists operate in the market, the above expression $[P(1 - P_P)] / (1 - P)$ would have a negative sign and would consequently be less than zero. Only optimists operate in the market for finance in equilibrium. They will self-finance as much as possible in order to minimise the amount they would have to repay, L_G, to the bank in the good state and select the smallest amount of borrowing possible, representing the shortfall in their capital requirements $K - W$, and post all their wealth as collateral.

There are several conclusions of the DM-S model that have implications for credit rationing. Firstly, the bank places importance on collateral. The entrepreneur because of his biased expectations of future wealth W_E is keen to over-invest in his project by investing an amount of capital K_H in excess of the necessary capital K^*. Individuals with higher initial wealth, W_H, can borrow enough from the bank to allow them reach the level of desired over-investment. However, individuals with initial wealth, $W < W_H$ cannot borrow as much from the bank as they would like and can only invest K^* in the project. *These individuals with less initial wealth will perceive themselves as credit constrained*. Irrespective of the willingness of 'undercapitalised entrepreneurs' to pay higher interest rate margins on their finance, the bank will not respond by increasing the amount loaned. DM-S maintain that entrepreneurs would be better off if investment were at the lower level K^* but they will tend towards over-investment on the basis of their inflated notions of the income generation capacity of their projects.

In view of the mistaken tendency of entrepreneurs to be overly sanguine about the expected profitability of their projects, DM-S argue that banks are correct to limit the flow of funds to enterprise. The authors argue that far from being credit constrained, entrepreneurs are only receiving actuarially fair amounts of funding for their projects.

2.46 The Petersen and Rajan (1995) model

The decision tree below best illustrates Petersen and Rajan's (1995) model **(Figure 2.5)**. There are two types of entrepreneur, good or bad. The projects of bad entrepreneurs are doomed to fail. However, good entrepreneurs can choose to invest capital K_0 in a safe project yielding income of Y_{1S} at the end of the period. He will then be able to invest capital of K_{1S} on a rollover basis in another safe project yielding income of Y_{2S} at the end of the second period. Alternatively the entrepreneur could invest the same capital K_0 in a risky project yielding income of Y_{1R} at the end of the period with probability P. The downside of taking this action is that this project could fail and yield zero profits with probability $(1 - P)$.

The P-R model makes the following assumptions. Firstly, that the safe project has a positive net present value while the risky project has a negative net present value. The net present value of the safe project is expressed as the income generated by the project minus the financial inputs into the project. This is expressed as follows;

$$Y_{2S} + Y_{1S} - (K_{1S} + K_0) > 0 \qquad \textbf{46.1}$$

For the risky project the net present value is expressed as;

$$P\,(Y_{2R} + Y_{1R} - K_{1R}) - K_0 < 0 \qquad \textbf{46.2}$$

A further assumption is that the expected value of the returns from undertaking either of the two projects is the same. This is expressed as follows;

$P(Y_{2R}) = Y_{2S} > P(K_{1R}) = K_{1S}$ **46.3**

The final assumption made is that the entrepreneur needs bank finance to undertake projects in the second period as the revenue generated in the first period is not enough to finance the second period project.

$K_{1S} > Y_{1R} > Y_{1S}$ **46.4**

Like all the models that have gone before with the exception of the DM-S model, the P-R model deals with asymmetric information. This means that the entrepreneur knows more about his probability of succeeding than does the bank although the bank knows the percentage of entrepreneurs in the past who have failed and succeeded. This percentage of past creditworthy firms is denoted by θ and is the quality, risk type or ex ante failure probability of the firm[21].

The basis of the P-R model is that the creditworthiness of the entrepreneur is only revealed after the initial investment of K_0 has been made in either a safe or risky project and the first period has elapsed. This model is most like the J-R model because it assumes 'transitional credit rationing' where good firms would prefer take a lower loan in exchange for more favourable interest rates in the second period. Once good firms know that the bank knows they are creditworthy at the end of the first period;

'good firms will borrow as little as possible at date 0 so that they can take advantage of the lower rate at date 1 when the bad entrepreneurs have been exposed'[22].

A central component of the P-R model is the measure of market power that they use. This is the bank's expected rate of return Y^{BANK}. It is 1 if the bank maintains a zero interest rate, r, under perfect competition and hence earns zero profits i.e. $Y^{BANK} = (1 + r)$.

P-R assume that an entrepreneur must earn some positive return on the project surplus, otherwise there would be no point in going into business. Therefore the return from undertaking the safe project, Y_{2S}/K_{1S}, must be higher than the bank's return Y^{BANK}. This is expressed as follows;

$Y_{2S}/K_{1S} > Y^{BANK} \geq 1$ **46.5**

The P-R model draws on the S-W model where it indicates that the bank should not charge such an interest rate in the first period that would encourage risk taking behaviour by the firm (moral hazard problem). Otherwise *the bank would be forced to ration credit if it could*

[21] θ is also used in the S-W model. The corresponding notation we used describing θ in the DM-S model is P but we cannot use P in the P-R model because P is also used as the probability that a risky project will fail

[22] P.411 Petersen and Rajan (1995)

<u>not structure its loan terms in such a way that firms self-select and take the low-risk contract</u>.

The firm only borrows capital K_0 at date 0. If the safe project is chosen, then the firm must borrow $K_{1S} - (Y_{1S} - L)$ to fund investment in the second period. $K_{1S} - (Y_{1S} - L)$ represents the shortfall in second period investment, K_{1S}, after the proceeds of the first period, Y_{1S}, are ploughed into the business and L, loan repayments for first period investment, K_0, have been repaid.

The entrepreneur's expected profit from undertaking the safe project represent the income generated by the second period project, Y_{2S} minus the repayments on the loan used to finance the second period project $K_{1S} - (Y_{1S} - L)$. The interest repayments on this second period investment guarantee the bank's rate of return Y^{BANK}. Therefore, the expected profit to the firm from undertaking second period investment in the safe project are as follows;

$$E(\pi)_{SAFE} = max\ [\ Y_{2S} - Y^{BANK}(\ K_{1S} - (Y_{1S} - L)),\ 0] \qquad \textbf{46.6}$$

The returns to the entrepreneur from undertaking the risky project where P is the probability that the project fails, Y_{2R} denotes second period income generated by the project, K_{1R} represents capital invested in order to generate second period income and $(\ K_{1R} - (Y_{1R} - L)$ represents the amount borrowed from the bank in the second period, is;

$$E(\pi)_{RISKY} = max\ [\ P\{Y_{2R} - Y^{BANK}(\ K_{1R} - (Y_{1R} - L))\},\ 0] \qquad \textbf{46.7}$$

The entrepreneur has an incentive to choose the safe project if the difference in the expected returns between the safe and risky projects divided by the likelihood of achieving zero return on the risky project is at least equal to the value of the first period loan repayments, L. This is expressed as follows;

$$[Y_{1S} - P\ (Y_{1R})]\ /\ (1 - P) \geq L \qquad \textbf{46.8}$$

The bank must structure the loan contract in such a way that the entrepreneur will prefer to undertake the safe project i.e. the bank uses the above inequality in order to formulate the terms of the loan. However, there is another constraint that the bank is aware of when formulating the loan terms. It must also recover its initial investment K_0. The bank will only lend if it knows that it can earn positive profits when the income generated by second period finance is recouped. This second period income is denoted by the amount of borrowed capital needed to fund second period investment, $(K_{1S} - Y_{1S})$, multiplied by the bank's return on the investment.

A further consideration is that the bank must also recover its first period loan plus repayments $K_0 / \theta\, Y^{BANK}$.

$$L \geq [K_0 / \theta\, Y^{BANK}\ ] - [\ (Y^{BANK} - 1/\ Y^{BANK})\ (K_{1S} - Y_{1S})\ ] \qquad \textbf{46.9}$$

A way of understanding the above inequality is to imagine what would happen if I replaced the terms with hypothetical values. For example, we would expect lending to become more lucrative for the bank if it had enough monopoly power to charge high rates of interest on second period borrowing. Hence the value for Y^{BANK} would be high making the first term K_0 $/\theta\ Y^{BANK}$ lower. Higher values for the bank's expected return, Y^{BANK}, make the expression $(Y^{BANK} - 1/\ Y^{BANK})$ tend towards unity. The overall effect of high interest rates in second period finance would be to make the right hand side of the inequality smaller and hence make lending more lucrative for the bank.

Another way of interpreting the above inequality is to consider what would happen if the entrepreneur were relatively more dependent on the bank for second period finance. This is another way of measuring the monopoly power of the bank. If the business is more dependent on the bank, it borrows considerably more in the second period because the gap between the income it generated after the first period Y_{1S} and the capital it needs to invest in the second period K_{1S} is larger. Hence the greater disparity between the desired level of second period investment K_{1S} and the available cash to plough back into second period investment Y_{1S}, the lower the value of the right hand side of the inequality and the more likely is the bank to finance the firm.

If the entrepreneur's incentive constraint (to choose the safe project) is substituted into the bank's profit constraint, the result is that only entrepreneurs with credit quality of at least θ (Y^{BANK}) will get financed by the bank. The notation for this is as follows;

$$\theta(Y^{BANK}) \geq [K_0(1-P)]/\ [Y^{BANK}(Y_{1S} - P(Y_{1R}) + (Y^{BANK} - 1)(K_{1S} - Y_{1S})(1-P)] \qquad \textbf{46.10}$$

The main conclusion we can draw from the above is that as bank monopoly power increases, as witnessed in higher values of Y^{BANK}, then the right hand side of the expression tends towards zero. The result is that as bank monopoly power increases, lower quality entrepreneurs (entrepreneurs with lower values of θ) tend to get financed. The implication of this result for credit constraints is that the availability of credit and existence of credit constraints should be decreasing in bank monopoly power.

2.47 The Evans and Jovanovic (1989) model

This *'switching'* model is possibly the most elaborate of the models.

The main assumption of the E-J model is that the entrepreneur's demand for a loan, *L*, is a function of his ability, θ, where higher skilled entrepreneurs have a higher demand for finance. If finance, *L*, is unconstrained ,then the E-J model donates it as L^*. This implies that the demand function for finance is described by the concave function $L^*(\theta)$ where L is increasing in θ (**Figure 2.6**). Profits, π, are also increasing in ability θ. They are negative at low levels of ability θ but cross the x-axis and become positive at higher levels of entrepreneurial ability. The function $\pi^*(\theta)$ shown by the grey line in **Figure 2.6** shows the profit function when the loan amount, L, is not constrained.

The E-J model depicts the desire of the entrepreneur to switch from wage to self-mployment as a density function, $\varphi(\theta)$, where the area under the function represents the probability, P, that an entrepreneur will make the switch. This probability depends on the profitability or survival of his business. It is self-evident that if the business is destined to make losses, then the entrepreneur will not consider self-employment as a viable option.

Now that I have described the main components of the E-J model; the demand for finance $L^*(\theta)$, the profitability function, $\pi^*(\theta)$, and the switching function, $\varphi(\theta)$, I turn to what happens when finance is constrained. When finance is constrained, the bank extends only a portion of the entrepreneur's demand for finance. This portion, b, is greater than zero and can be either a fraction or integer. The bank lends in proportion to the firm's assets, C. An entrepreneur with ability θ_1 will demand finance equivalent to bC_1. Entrepreneurs of ability θ_2 will demand finance equal to bC_2, and so on. The E-J model does not state where θ_4, corresponding to a demand for finance of bC_4, lies. However, we are informed that entrepreneurs demanding this level of finance and having an ability level, θ_4, that is commensurate with a demand for finance of this magnitude, are not constrained. Instead they switch from wage to self-employment with probability P_2 (where the profitability function, $\pi^*(\theta)$, intersects the x-axis).

The marginal entrepreneur who earns zero profits, has an ability of θ_2. The model hypothesises what would happen if the bank offered this entrepreneur an amount of finance, bC_1, that is less than the finance demanded by this entrepreneur, bC_2. In this case, the entrepreneur is constrained because he cannot earn the level of profits commensurate with his ability and must satisfy himself with a less than optimal level of finance. His probability of switching from wage to self-employment decreases from P_2 to P_1 as a result.

The prediction of the E-J model following from the above is that if assets, C, are found to be positively correlated with the level of start-ups, then credit constraints exist because what is being measured is the propensity of the marginal entrepreneur, θ_2, to enter self-employment. His probability of switching diminishes if he has a level of collateral, C, that does not permit him to leverage his optimal level of finance, bC_2 (analogous to the imposition of tougher collateral to loan amount ratios). This credit gap or constraint should be reflected in a positive relationship between collateral (or assets) and the likelihood that marginal firms will make the transition to self-employment.

2.5 Summary of the *borrower reputation* models

The issue of borrower reputation deserves a separate section because the influence of borrower reputation on the price or availability of credit is a specific application of the credit constraints models described above. We have seen in **section 2.4** that a lender can decide to reduce credit to borrowers as a result of information asymmetries. The reverse side of the coin is that the lender can opt to relax the rules that operate where information about the borrower is limited or asymmetric in the case *where the borrower's credit history is known*. Borrower reputation models show the dichotomy arising when borrowers are treated differently because the bank knows their creditworthiness. These models therefore distinguish between first- and second-period borrowers where the bank knows more about the creditworthiness of second-period borrowers[23].

The literature, which predicts the effect that business-bank relationships have on the price of credit, is divided into two opposing viewpoints. Some of the models predict that in the first borrowing period, interest rates will be lower than in the second borrowing period (Greenbaum et al, 1989; Sharpe, 1990). On the other hand, Boot and Thakor (1994) have developed a model that predicts the completely opposite effect on interest rates whereby a bank commences lending at a comparatively higher rate than in subsequent periods. We now explain how these opposing conclusions have been arrived at.

All theorists make assumptions about two main environmental conditions. The first assumption concerns how competitive the market for finance is. The second assumption relates to the degree of information asymmetry in the lending market. This second assumption has to do with how observable the creditworthiness of the borrower is in the first and subsequent lending periods, respectively. In other words, can other banks observe the creditworthiness of the borrower after the first bank has completed its initial investment in the business?

All the models reviewed here assume that private information collected by the bank about the borrower's creditworthiness cannot be passed on to other lenders in the second period. Positive gains arising through reduced information-monitoring costs and reduced borrower default risk accrue to the bank. The bank can either decide to pass these gains on to the

[23] Another word for first-period borrowers that I use in **Chapter 7**, is *'through-the-door'* borrowers.

borrower or not in the second borrowing period, depending on the level of monopoly power exerted by the bank and correspondingly the level of interbank-competition.

Petersen and Rajan (1995) assume that an environment of private information is symptomatic of low levels of competition in the lending market. Boot and Thakor (1994), Sharpe (1990) and Greenbaum et al. (1989) assume that a private information environment prevails in the loan market in conjunction with high levels of interbank competition. Diamond (1989) makes no assumption regarding the degree of competition.

I can now summarise the different predictions of the reputation models for interest rate margins. The Boot and Thakor (1994) and Diamond (1989) models predict that interest rates in the first period will be higher than interest rates in the second period. In other words, the B-T and Diamond models predict that interest rates are negatively related to the length of a business-bank relationship. On the other hand, the models by Greenbaum et al. (1989) and Sharpe (1990) predict that interest rates are positively related to the length of a business-bank relationship. In other words, that the interest rate for second-period finance is higher than the interest rate charged for first-period finance. The Petersen and Rajan (1995) model (that was also discussed in **section 2.4**), predicts that the rate charged for second-period borrowing in a concentrated market is higher than the rate that would be charged for second-period finance if the market were more competitive.

Each model emphasises a different feature of the lending contract. We first look at the models that predict higher interest rates in the second period because they have some similarity in their design.

The basic design of these models is to indicate that interest rates in the first period will be low to attract new customers because, under competition, a business has a choice from which bank to borrow. Information about the creditworthiness of the businesses is at a minimum. Once the business has undertaken to borrow from a particular bank, the bank can generate 'private information' on the borrower that cannot be observed by other banks. The business's dependency on the bank therefore increases, thereby allowing the bank to recoup some of its initial losses from first-period lending, in subsequent periods. The business cannot escape from monopoly interest rates charged in subsequent lending periods because it is in a sense *'informationally captured'* by its lender (Sharpe, 1990). Even if other banks wanted to make themselves attractive to *'informationally captured'* borrowers, they would run the risk of adverse selection. If the bank is able to exercise this market power, the market for lending is inefficient.

Now we come to what features differentiate the models that predict higher second term interest rates. Petersen and Rajan deal primarily with bank concentration as a driver of these inefficiencies. Sharpe focuses on implicit contracts as a way of circumventing the inefficiencies above. On the other hand, Greenbaum et al. deal among other things, with the exit costs which would be incurred by a second -period borrower. These costs would offset the financial gains in the form of reduced interest rates from moving to a competing bank.

The Petersen and Rajan model focuses on market concentration where an absence of competition between banks permits the bank to skim off the borrower surplus in subsequent periods and thereby earn monopoly profits. Interest rates in the second period are therefore higher than interest rates in the first period. The degree of banking concentration is an exogenous variable which influences the magnitude of second-period interest rates. The level of bank concentration also influences the extent to which the bank can use its information monopoly on the borrower to drive up interest rates in the second period. While other models assume that market concentration is ancillary to, or a by-product of, a lack in lender competition, Petersen and Rajan highlight it as an important influence in its own right.

The Petersen and Rajan model fails to allude to the circularity between market concentration and information monopolies. If banks enjoy information monopolies, this prevents the borrower from switching to other banks because the original lender exercises a monopoly over the borrower. If the originally lender additionally enjoys a first-mover advantage over other lenders in the market for credit, information monopolies will drive other lenders out of the market and reinforce the level of banking concentration. Information monopolies and market concentration are self-reinforcing, with the assumption of first mover advantage.

In the Sharpe model, the bank is more proactive in its retention of the customer. Rather then let market forces decide the fate of the borrower as in the Petersen and Rajan model, the original lender can attempt to create a contingent contract where second period interest rates are conditioned on the performance of the borrower in the first period. This incentive approach employed by the lender in the Sharpe model is analogous to the approach used by Jaffee and Russell (1976), described in **section 2.4**. In J-R's model, it is the amount rather than the interest rate, which in the second period is conditioned on borrower performance.

There is an incentive for the bank not to cheat on the contract. This incentive arises if the net present value of retaining the customer and charging interest rates in excess of the marginal cost of finance to the bank, is greater than the short run monopoly profit the bank would earn by reneging on its agreement. It would renege on its agreement by not reducing the interest margin, despite the borrower proving himself to be creditworthy.

Sharpe acknowledges that in reality, contingent contracts are expensive and difficult to operationalise. In addition, Sharpe argues that the original lender should make use of implicit contracts (non-binding promises that the borrower will remain with the original lender if the original lender recognises his loyalty through preferential interest rates). Although, implicit contracts (ICs) represent a cheaper and less formal alternative to explicit contracts, it is doubtful that they would reduce market inefficiencies from the current level of inefficiencies in the absence of implicit contracts. A first-time business borrower would have less experience evaluating a bank's ex ante honesty than a bank would have evaluating that of a business. It is unclear how exactly the bank could establish its own reputation because subsequent borrowers do not necessarily know how the bank treated their predecessors. The success of ICs in counteracting market inefficiencies would likewise suffer information asymmetries. The inability of a borrower to rate a lender is most likely higher than the inability of a lender to evaluate the borrower.

The model by Greenbaum et al. that predicts that interest rates increase in the second borrowing period, focuses on the exit costs for second period borrowers as being a major factor in preventing second-period borrowers from reapplying elsewhere. Exit costs in this model can be interpreted as the search and evaluation costs incurred by a borrower wishing to switch banks. They argue that the price the lender bank charges on the bank loan is higher than that charged by the competitors. This monopoly profit arises not just because of the monopoly power conferred by private information but also due to the cost the borrower would incur in searching for, and evaluating a loan proposal, from another bank.

The Greenbaum et al. model therefore differentiates itself from the other models by considering borrower exit costs. However, there is a finite length to a bank borrower relationship. The longer that a borrower is *'informationally captured'*, as Sharpe describes the dependency of the business on the bank, the greater the incentive for the business to cut itself free from the relationship. Therefore, the longer the relationship between the bank and borrower, the higher the interest rate and the higher the likelihood that the borrower will transfer to another bank.

The advantage of the Greenbaum model over the others predicting a positive association between interest rates and relationship, is its inclusion of borrower exit costs into the model. At some stage, the marginal benefit to the borrower of exiting the dependent relationship is greater than the marginal cost of searching out an alternative source of finance. Unlike any of the other models, the Greenbaum model therefore sees the relationship as a finite one with a certain time horizon. The marginal costs of remaining in the relationship increase over time until it becomes no longer viable for the borrower to continue to pay above average interest rates.

Finally, we evaluate the theoretical models that infer that there is a negative relationship between the length of the bank borrower relationship and interest rates. Boot and Thakor (1994) describe a repeated credit market game where all banks initially charge high interest rates to first-time borrowers. It is only when the borrower has proved itself and survived until the second borrowing-period that the lender relaxes the initially higher interest margin and charges interest rates which are commensurate with the risk type of the business.

What induces the bank to pass on the benefits of lower borrower risk to the borrower in the form of lower interest rates? The answer lies in the competitive banking environment. If the bank does not lower interest rates in the second period, then the borrower will be tempted to leave for a competing bank.

A difficulty with the B-T model arises when the model justifies borrower retention by competitive forces. The model assumes that a borrower has the option in the second period to move to another bank. However, the model does not consider that the other bank is not privy to the private information generated by the original lender. Since the authors assume private information, they do not indicate how the business can convey its creditworthiness to the competing bank. For this reason, the B-T model is unrealistic if information generated by the original bank is not transmitted to other banks following the successful amortisation of the loan by the borrower. However, if survival and firm age are more important factors driving the interest rate (external and verifiable attributes of the borrower), then the B-T model is possibly the best model at describing the influence of the borrower-lender relationship on interest rates.

The Diamond (1989) model, like the Boot and Thakor model, predicts that interest rates are lower for second-period borrowers. Diamond assumes a multiperiod framework entailing a game where it only pays a borrower to develop a reputation once a borrower has survived the first period of borrowing with high interest rates. A core assumption of Diamond's model is that a borrower develops a public reputation in the form of a credit rating that can be accessed by competing banks. However, a difficulty with Diamond's model is that such public information as that contained in a credit rating is not costless. Diamond does not take into account therefore, that the original lender is still placed at a price advantage relative to other banks because it already knows the credit rating of the borrower without having to pay a credit bureau for this information. Therefore, costless information about the borrower is still unavailable to other banks after the first borrowing period and hence a '*private information*' environment still prevails.

To sum up this section on borrower reputation, on balance, the theory is equally divided as to whether borrowing in the first period will be cheaper for a borrower compared to second-period borrowing.

2.6 Conclusion

In this chapter I have presented and described the theoretical literature on bank lending. I will now summarise the main conclusions we can draw from a review of the literature.

Firstly, rationing exists in several forms. Using the terminology first used by Besanko and Thakor (1987a), '*transitional*' rationing occurs when the amount loaned is staggered over two periods and the second tranche of finance is extended by the bank when the borrower's credit status becomes known. Papers suggesting this form of credit rationing are by Jaffee and Russell (1976) and Petersen and Rajan (1995). '*Equilibrium*' credit rationing also occurs under conditions of asymmetric information but in this case borrowers have their full borrowing requests turned down. This form of credit rationing is used as a deterrent in order to dissuade borrowers of a certain risk type from applying for a credit contract not intended for them by the bank. Papers indicating this type of credit rationing are by Stiglitz and Weiss (1981), Bester (1985) and Besanko and Thakor (1987b).

These two alternative interpretations of credit rationing are mutually exclusive, Stiglitz and Weiss (1981) argue that '*transitional*' credit rationing cannot work because if the bank rations the amount of credit it gives to each individual firm, such under investment exacerbates the frailty of the firm. '*Transitional*' credit rationing is therefore argued to raise rather than decrease the risk of default by making the firm more vulnerable.

Apart from the '*transitional*' and '*equilibrium*' models of credit rationing, the De Meza and Southey model (1996) suggests that credit constraints are illusory and only arise because entrepreneurs are excessively confident. They predict that <u>low quality, high-risk entrepreneurs (optimists) demand more finance</u> than high quality, low-risk entrepreneurs (pessimists). The DM-S paper reverses the information bias in favour of the bank rather than the firm. Therefore, the type of credit constraints they depict are illusory because they are due to the subjectivity of the entrepreneur's assessment of the amount of finance he requires for his project. The '*switching*' model by Evans and Jovanovic (1989), contrary to the predictions of the DM-S model, predicts that entrepreneurs of higher ability request comparatively high levels of finance compared to their low ability counterparts.

The second main conclusion relates to the interplay of collateral and interest rates. All post Stiglitz and Weiss papers recognise the contribution of the S-W model postulating that because of moral hazard and adverse selection problems, raising interest rate margins is not an effective way of pricing borrower risk. The S-W paper underpinned the role of collateral in providing repayment incentives and in inducing borrowers to undertake lower risk projects. Bester (1985), Besanko and Thakor (1987a, 1987b) and Evans and Jovanovic (1989) include collateral in their model of credit constraints. However, the most recent papers by de Meza and Southey (1996) and Petersen and Rajan (1995) concentrate on credit constraints for uncollateralised borrowing.

The final conclusion of this chapter on the theoretical literature of asymmetric information concerns the predictions of the models dealing with borrower reputation effects. The Boot and Thakor (1994) and Diamond (1989) models predict that interest rates in the first period will be higher than interest rates in the second period. On the other hand, the models by Greenbaum et al. (1989) and Sharpe (1990) predict that the interest rate for second-period finance is higher than the interest rate charged for first-period finance. The Petersen and Rajan (1995) model predicts that the rate charged for second-period borrowing in a concentrated market is higher than the rate that would be charged for second-period finance if the market were more competitive. On balance, the theory is equally divided as to whether borrowing in the first period will be cheaper for a borrower compared to second-period borrowing.

Figure 2.1 J-R model; credit rationing at point E

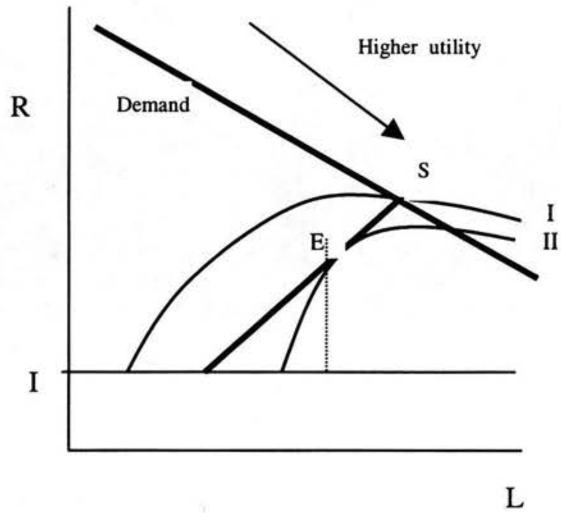


Figure 2.2 S-W model; optimal interest rate r_1

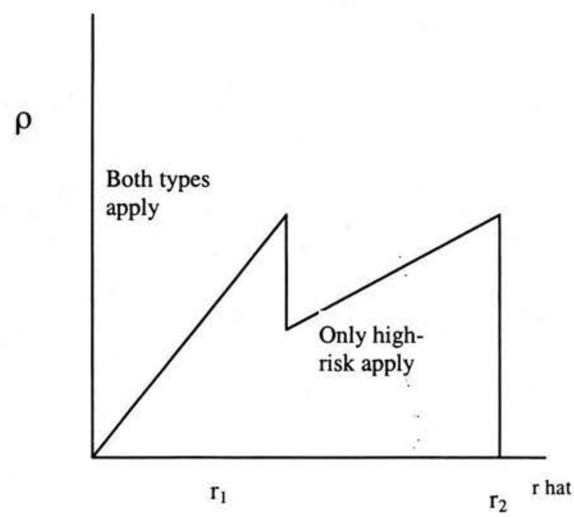


Figure 2.3 S-W model; determination of the market equilibrium

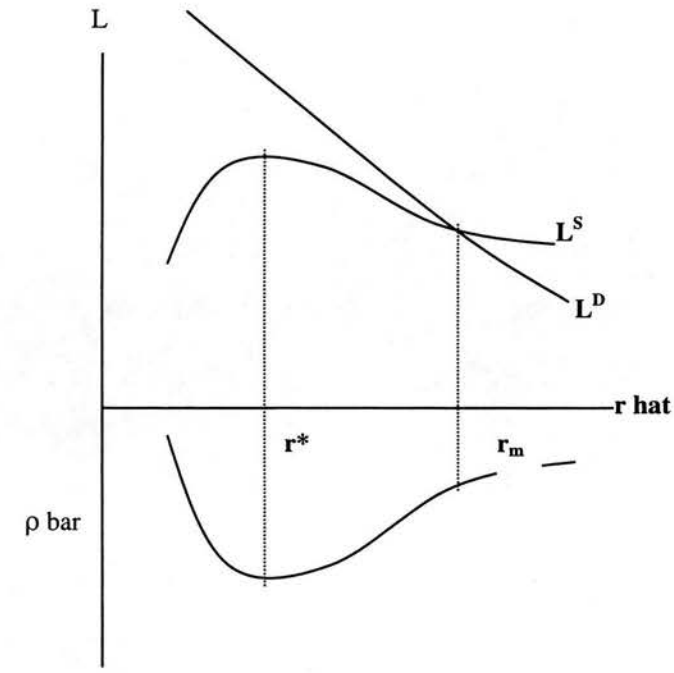


Figure 2.4 Bester (1985) model; equilibrium with costless C

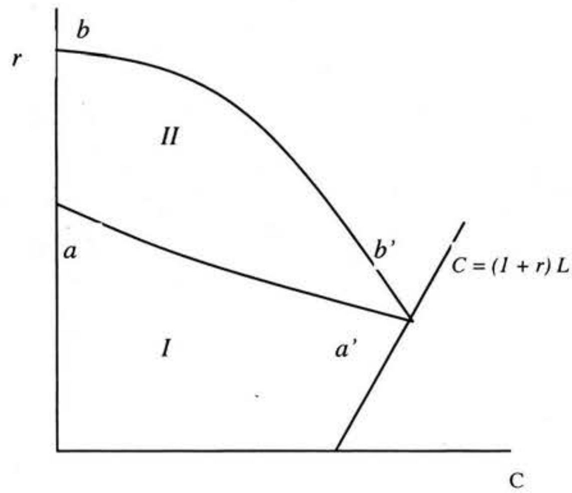


Figure 2.5 Petersen and Rajan model scheme

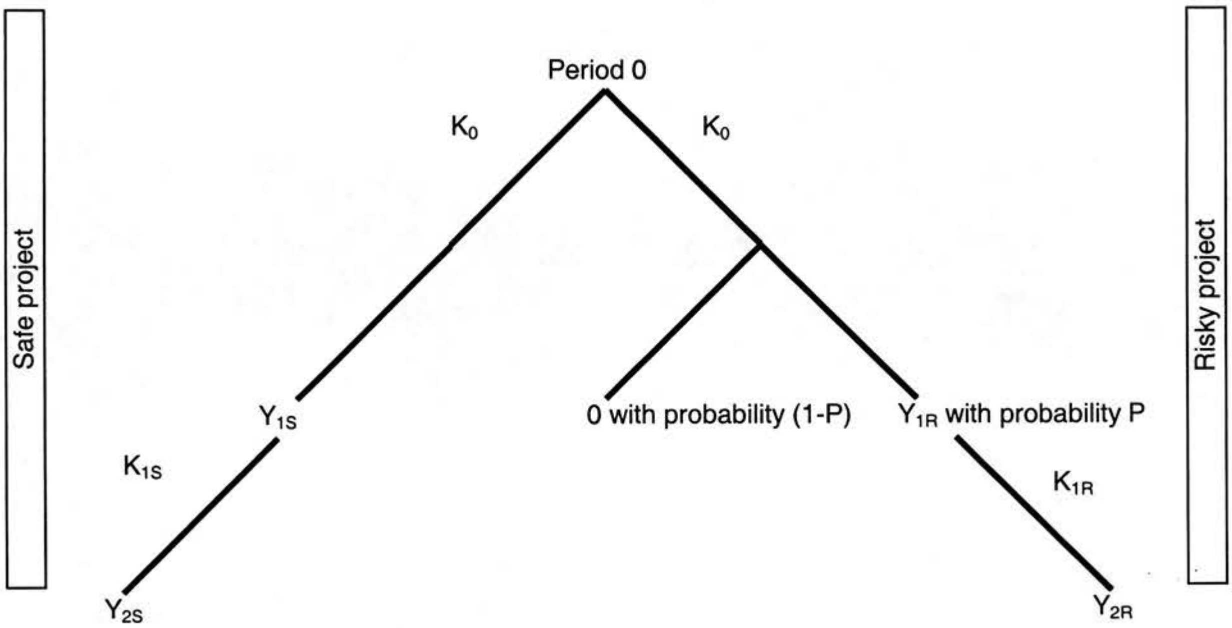
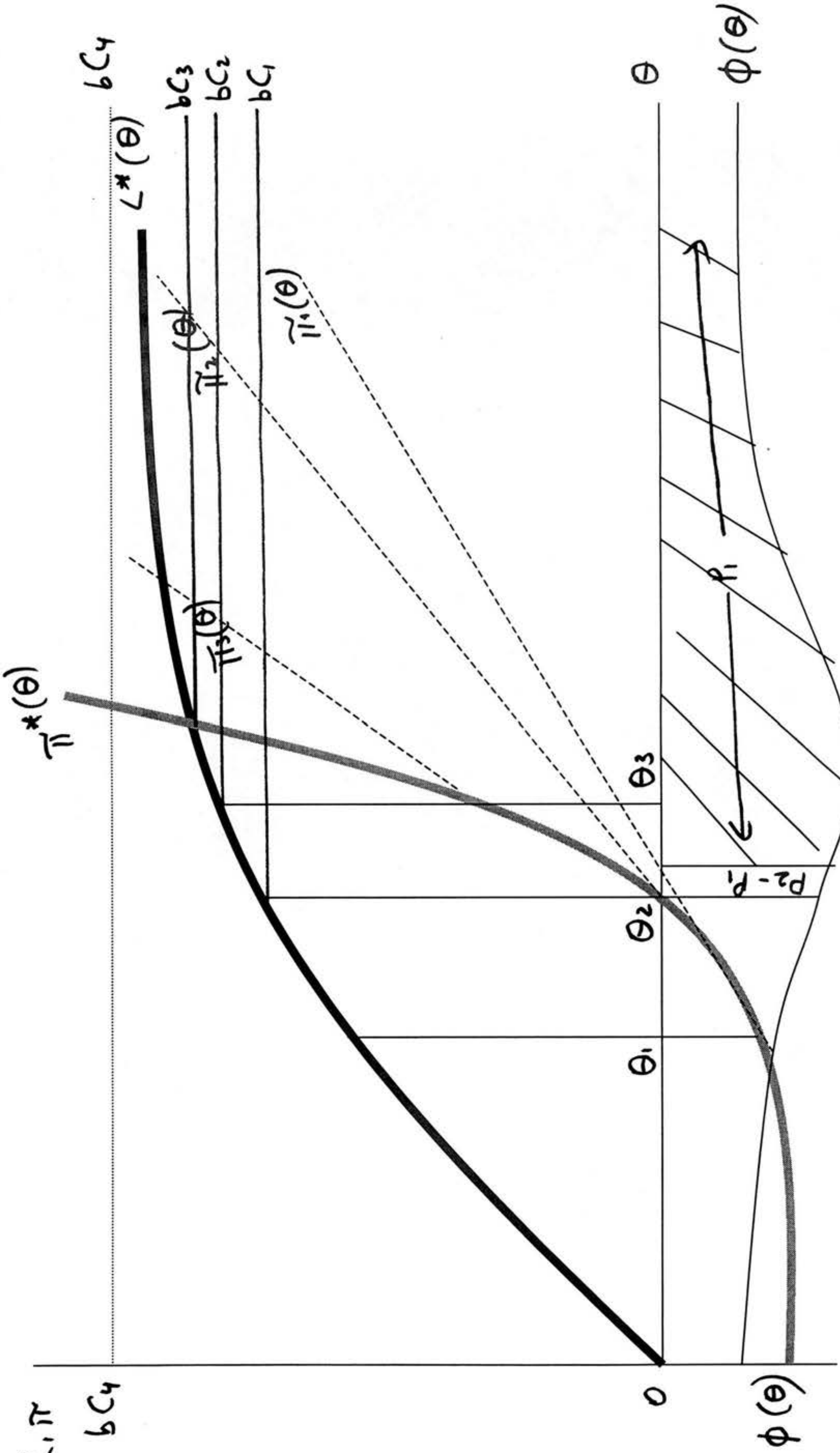


Figure 2.6 Switching in the E-J model



Chapter Three

Methodology of estimating credit scorecards

3.1 Introduction

The aim of this chapter is to prepare the background for my subsequent empirical chapter where I estimate a commercial scorecard predicting the likelihood that a small business borrower is diagnosed by a bank's credit department to be irredeemably uncreditworthy.

I will explain what credit scoring is and how it is carried out and I also will attempt to present and elaborate on some of the main issues in scoring commercial businesses that are relevant to my subsequent research.

I should note a qualification here for readers with a theoretical background. Credit scoring is a predictive and not a theoretical science. It does not set out to explain why certain variables (characteristics as they are referred to in credit scoring) are seen to be closely related to the response variable. This means that the literature of credit scoring does not contain theoretical economic models nor scientific explanations of why certain phenomena act as they do.

This term 'credit scoring' comes from the summated rating scale methods that are still widely used in the industry (Hand, 1997). Credit scoring as a science has been widely practised since the 1980's. While the practice of scoring large corporations based on a few accounting indicators is widespread, there is little published work on how small businesses are scored (Hand, 1997; Crook et al, 1992). However, I should draw a distinction between the scoring of small businesses and the scoring of large corporations. In the latter case, there is a vast literature dealing with the prediction of bankruptcy as pioneered by Altman (1977). However, the aim of my research is not to perform a bankruptcy study. Rather my research is a study, the first of its kind aiming to derive a credit card predicting severe borrower default for first-time small business applicants. Rather than using financial ratios to predict the response variable as bankruptcy studies do, I use the application characteristics of the borrower, alongside straight accounting information, to predict default as proxied by credit grade rather than bankruptcy.

A further reason for gaps in the area of research into credit scoring is the high levels of secrecy observed by individuals who estimate scorecards on behalf of a bank or such organisation. According to Crook et al (1992) much work is carried out by practitioners rather than academics and according to Hand (1997) these practitioners observe high levels of secrecy. The result of these two features of the credit scoring literature is that to date only a few direct or indirect analyses of small business credit scoring exist (Altman et al. 1994; Leonard, 1992; Srinivasan and Kim, 1987; Asch, 1995). This is not to say that scorecards have not been estimated for small businesses. On the contrary, the scoring of small businesses is an everyday feature of lending in the highly competitive US market (Mester, 1997; Fair, Isaac and Co, 1999; Hanley, 2000). However, competitive pressures have meant that little is known about the construction or efficiency of small business scorecards that use application characteristics rather than a zeta score as the explanatory variables. Asch's study is typical of the type of practitioner's analysis that is careful not to violate secrecy laws. He discusses the US small business scorecard that was derived by the Fair Isaac Corporation using a proprietary database (from Richard Morris Associates) without presenting the significance levels of any of the variables used in the estimations. He also does not indicate the default measure used in estimating the small business scorecard, show how it was derived or how the data used in the estimations was aggregated.

One of the aims of my research is to address this deficiency in published work on small firm scoring by estimating my own scorecard based on data from a UK small business database. For the first time in the literature I discuss how the data was aggregated, which application data was used and how problems such as missing values and low default and estimation sample frequencies were addressed. I also present the explanatory variables that were found to be most significantly correlated with default and attempt to explain why they are important.

In this chapter I introduce the reader to the technique of credit scoring and explain how the robustness of different scorecards is evaluated. This chapter contains, therefore, a generic description of credit scoring without assuming how the scorecard is to be applied.

3.2 Background to credit scoring

In the following sub-sections, I will describe the basic principles of credit scoring. I will highlight what I consider to be the most important aspects of credit scoring, where they affect my own analysis. The most important issue in my opinion, concerns the evaluation of how discriminative or good the scorecard is and the different tests that can be performed to ensure that the scorecard is robust. This will be described at length because the validity of a scorecard model is not influenced by any theoretical considerations but rather by how well it discriminates between firms that default and firms that do not default.

3.21 What is credit scoring?

Credit scoring, in its simplest sense, is where a bank lending to a new applicant wants to know the likelihood that the applicant will repay this new loan that the bank has granted.

The bank infers its decision to grant the loan based on the correlation between the probability that a similar loan is repaid and the application characteristics of other, similar borrowers who have been granted first-time loans. By deriving this relationship between repayment/default probability and the application characteristics of first-time borrowers, that bank has an application scorecard. This type of scoring is known as application scoring because applicant is applying for a first-time loan and the bank has no detailed history of how the borrower has made repayments on a similar type of loan. Each response on an application form is assigned a value and the sum of these values for an individual is that individual's overall score. This value is compared with a threshold or cut-off value in order that the bank is able to reject or accept the applicant.

On the other hand, the bank can score existing customers by extrapolating how likely these borrowers are to exhibit default based on their current repayment behaviour (Hand and Henley, 1997). For example, they may frequently use the full amount of their overdraft (known as drawing down their full credit limit). If this behaviour is strongly correlated with subsequent default, the bank will act on this information and contact the borrower to inquire about his working capital situation. Such scoring is known as behavioural scoring[1].

Since my analysis in **Chapter 6** aims to derive an application rather than a behavioural scorecard, the remainder of this discussion concerns itself with application scoring alone.

In reality, the distinction between application and behavioural scoring models is blurred when combinations of both credit bureau data and application details are used in credit scoring models. What differentiates the two techniques, is not so much the left-hand side variables but the predictor variables i.e. the right-hand side variables. The question to ask is whether the analyst needs the model to select new customers (application scoring) or to rate existing ones (performance scoring) in order to provide them with a credit extension or to adjust the terms of their loan.

An application credit scoring model without behavioural data lacks predictive ability and this is the reason good credit bureau data is useful in constructing scoring models. Chandler and Johnson (1991) correctly classify a maximum of 50 percent of cases using population proportions. Using simple credit bureau data the overall prediction rises to approximately 70 percent. Wiginton (1980) reports similar results for a dataset that does not contain any

[1] An example of performance scoring is seen in the consumer credit analysis by Crook, Hamilton and Thomas (1992). Here the likelihood of an account turning "At least three cycles delinquent" cycles delinquent is estimated given that the accounts had already been "One and two but not three cycles delinquent". Studies using credit bureau data have also a performance component because accounts are rated based, inter alia, on their past repayment behaviour and credit rating.

performance data. Wiginton finds that estimating a scorecard based on application data alone achieves disappointing results. He argues that:

"..data typically obtained from credit applications and used to develop scoring models are not sufficiently relevant to be of real value in making unaided credit-granting decisions"[2].

3.22 Separation of creditworthy from uncreditworthy customers

We now look at the technical side of credit scoring. In Crook, Edelman and Thomas (1992), the bank wants to establish whether the likely subsequent credit behaviour of the borrower will be acceptable or unacceptable to the bank. If the likely subsequent borrower behaviour is deemed acceptable it is classified as a good. The corollary to this is that a borrower is deemed unacceptable and is classified as a bad.

It follows that if A is the set of all application form data, a credit scorer will want to split A into two subsets A_G and A_B such that classifying applicants in A_G as good and those in A_B as bad minimises the misclassification error. The misclassification error would arise if applicants deemed by the bank to be good turned out to be bad (*Type I* error). Alternatively misclassification would arise if applicants that were predicted to be bad turned out to be good (*Type II* error).

A problem arises here concerning the type of estimation samples typically used in credit scoring studies. The credit scorer can get a measure of *Type I* error in my example above because this represents the percentage of default in the sample of applicants who were granted loans. However, gaining an estimate of the percentage of applicants that were turned down who subsequently turned out to be creditworthy is problematic. Therefore, *Type II* error is difficult to estimate, although techniques such as reject inference attempt to correct the model relating to accepted cases to account for this deficiency.

The reject inference issue arises in almost every scoring study. It does not arise when the scoring model uses data that has not been precensored, as in Wiginton (1980). This comparison of the predicted performance of logistic regression to discriminant analysis uses unscreened data. Wiginton makes the point that this precludes sample bias unlike most data used in scoring models that is already censored. In other words, by having been screened, weaker firms are underrepresented, a fact which confounds models[3].

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[2] P.758. *ibid*

[3] Korobow et al. (1976) provide another example of a scoring experiment, which uses unscreened data. They monitor the probability that commercial banks exhibit a low enough liquidity level to warrant a visit by US bank inspectors using logistic regressions. Their r^2 value of greater than 0.9 in both periods perhaps reflects the use of unscreened data but their research question i.e. monitoring existing banks is not of the type to cause screening problems.

Thomas (1998) and Cohen and Hammer (1966) suggest various methods that have been used to attempt to reduce this bias. One method is "augmentation" which involves building a linear function to discriminate between those that are accepted and rejected. For each score estimated by the linear function the proportion of those with a certain score who have been accepted by the bank is weighted proportionally to the inverse of their probability of acceptance. The weighted sample is then used to estimate the linear function, which differentiates between the goods and the bads. This weighting procedure assumes that the probability of an observation being a good, given that it has a certain score, is the same for accepted as for rejected applicants. In other words, that $P\ (g\ /x)$ is the same for both the accepts as well as the rejects. A full description of augmentation is contained in Banasik et al. (2001).

In the same paper, Banasik et al. examine the predictive accuracy of a bivariate probit model with selection (BVP) in order to overcome the problem of reject inference. This application of a Heckman (1979) model basically allows for the fact that the rejected applicant's cannot be observed in the data and attempts to correct for this bias in a 2-stage procedure. This paper is the most recent contribution to the area of reject inference. Banasik et al. (2001) find that their BVP model may improve accuracy if the loan officer has overridden a scoring rule.

Cohen and Hammer's (1996) remedy for this type of bias is more intuitive but perhaps not as practical. They suggest that the optimal way to deal with this bias is for the bank to lend to all customers for a period and not discriminate a priori between customers who they believe to be good and poor risks. The scorecard is then estimated on the unscreened customer data. They justify the increased losses, which would be incurred by the bank through increased default rates, by arguing that:

"The increased losses during this limited period should be regarded as part of the cost of gathering data for the development of an effective numerical credit scoring system[4] .

Despite the problems arising from using pre-screened samples to estimate scorecards from which the rejected applicants are omitted, *Type I* error is typically regarded as far more serious than *Type II* error. In other words, it is more important for a bank to reduce the percentage of its accepted applicants that eventually have their debt written off rather than to forfeit business customers who would have been creditworthy. Although, it can be argued that both types of loss are important, banks owe a duty to their depositors not to gamble with

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[4] P.130-131. Cohen K.J. and F.S Hammer, 1966. 'Analytical methods in banking'. Eds. K.J. Cohen and F.S Hammer

the money placed in their trust and therefore have to be seen to view *Type I* losses arising through company bankruptcy and insolvency as very serious.

Weiss (1996) puts the costs of misclassifying a bad relative to a good, where the response variable is bankruptcy, at 25/1. Altman et al. (1977) put the relative costs of misclassifying a bad relative to a good, again where the response variable is bankruptcy, at 35/1. Altman et al. therefore conclude that the cost of bankruptcy is even higher than the estimate provided by Weiss (1996). Using the cost estimates provided by Altman et al., we can infer that 35 loans to firms which do not go bankrupt (*Type II* firms), can be traded off against each loan to a bankrupt firm (*Type I* firm). Expressed another way, if a bank lends £100 to a firm that goes bankrupt, the bank loses £70 of the value of the loan principal. However, if the bank denies a loan of £100 to a borrower who would have repaid his loan, the bank incurs an opportunity cost of £2 (equivalent to the interest margin plus the underwriting fees). Weiss (1996) points out that this estimate by Altman et al., does not take into account the disparity in size of different business loans and assumes that they are homogeneous. Of course, the absolute loss to the bank if the borrower defaults on a large loan is higher than the absolute loss that the bank would incur on a smaller loan but this loss would not be reflected in a cut-off that relied on loans being homogeneous in size. If it happened that smaller firms who were more likely to request smaller loans, exhibited a higher default rate than large firms, the overall loss on the bank's portfolio would depend on the relative size of loans to SMEs as well as the disparity in their default rates. Weiss (1996) urges future research to be cognisant of the potential variation in loan sizes when calculating cut-offs. He argues that in the US, the bankruptcy rate never exceeded 0.75 percent since 1934 although this statistic relates to larger firms which are listed on the Stock Exchange. According to Barclay's Bank Information Service (2000), just fewer than 20 percent of start-ups fail in their first year of trading and over 60 percent in the first 5 years. We can conclude that there is considerable variation in default rates that would confound efforts to estimate sensible cut-offs for a heterogeneous sample of small, unlisted and large, listed businesses. The appropriateness of a cut-off really depends on the heterogeneous nature of the estimation sample being used.

So we have looked at classifying applicants into two subsets of the application dataset A, where applicants predicted to be good belong to the subset A_G and bad applicants to the A_B subset. The corresponding *Type I* and *Type II* errors that I have discussed above can be written as D and L respectively. D describes the loss arising from borrower default and L the lost profit from rejecting a good applicant. P_G and P_B are the proportions of good and bad borrowers in the population of applicants. In practice P_G and P_B are often established from those applicants who were granted a loan.

Let $P(x \mid G)$ be the probability that an applicant has characteristics x given that he is good. This is a conditional probability and it is written as follows;

$P(x \mid G) = P$ (applicant is G and has characteristics x) / [P (applicant is G)]

So by cross-multiplying we get the expression;

P (applicant is good and has characteristics x) = $P(x \mid G) * P_G$ **3.1**

The probability that an applicant with characteristics x is good $q(G \mid x)$, is also a conditional probability and so equals;

$q(G \mid x) =$

P (applicant has characteristics x and is G) / P (applicant has characteristics x) **3.2**

So from **3.1** and **3.2** we get;

$q(G \mid x) = [P(x \mid G)\, P_G] / P(x)$ **3.3**

An important concept to grasp in the above piece of mathematical notation dealing with the choice of the decision rule the bank will take, is the idea that the bank can only observe the past and not the future. In other words, the bank can observe the conditional probability that borrowers who turned out to be creditworthy, G, were associated with a score x. This can be expressed as the probability $P(x \mid G)$. Although this may seem a truism, it means that the bank can observe that a borrower who was creditworthy had particular application details. It is more useful for a bank to be able to infer whether applicants, given that they exhibit a particular score, x, will subsequently turn out to be creditworthy, G. In mathematical notation this reads as $P(G \mid x)$. This is the essence of prediction. In scientific notation this means that the bank can observe the good outcome of the borrower which is $p(x \mid G)$ where x is the application data exhibited by the borrower, G the good ex post outcome and p the probability of the outcome occurring. The same rationale applies to the bad outcome. The bank can look back in history, retrieve the defaulted borrower's files and establish that he had application data x while turning out to be a defaulter at a later stage. In mathematical notation this conditional probability translates into $p(x \mid B)$.

A slightly more difficult concept to explain is the predicted outcome. Of course this is the outcome we are really interested in because nobody cares to predict what has already happened. Of far greater importance is to extrapolate future creditworthiness from past outcomes. This concept lies at the heart of credit scoring. The ex ante outcome that is the probability of a person exhibiting application data x going on to become a creditworthy borrower is $q(G \mid x)$. This can be expressed as the following question; given that the borrower has application details x, what is the likelihood that he will turn out to be creditworthy? The corollary to this is the conditional probability for the bad borrower. This is written as

$q(B \mid x)$ where the probability of an applicant having application details x and subsequently turning out to be bad is described.

The assumption that we can predict the probability that an applicant with a certain score turns out to be creditworthy, $q(G \mid x)$, using the historic proportion of good applicants in the population P_G and the probabilities that such good applicants achieved a similar score x,

$P(x \mid G)$, is an heroic one to make. This is because it depends on the application data having the same relationship with the outcome variable in the time period in which the application data was collected (scorecard estimation period) as the relationship existing between the application data and the outcome variable in the unseen set of borrowers whose creditworthiness is being predicted. It also depends on the proportion of good applicants, P_G, remaining constant across the two periods. Because the relationships between the explanatory variables and the outcome variable can change over time, scorecards frequently need to be recalibrated to account for this attrition. Also, scorecards rarely try to infer the future behaviour of applicants at too distant a point into the future[5].

Because we have shown how conditional probabilities can be used to generate a probability that applicants exhibiting a certain score are good, let us now show how the credit scorer comes up with a decision rule. This decision rule incorporates information on the relative misclassification costs described earlier with the conditional probabilities described above. Essentially this decision rule shows the trade-off between the cost arising to the bank through default D and the lost profit arising from declining customers who turn out to be creditworthy L. The full expected loss arising is;

$$L \sum_{x \varepsilon A_B} p(x \mid G)\, P_G + D \sum_{x \varepsilon A_G} p(x \mid B)\, P_B$$

The product of the posterior probabilities by the proportions of good or bad in the sample can also be written as;

$$L \sum_{x \varepsilon A_B} q(G \mid x)\, P(x) + D \sum_{x \varepsilon A_G} q(B \mid x)\, P(x)$$

In order to minimise the total loss to the bank, the loan sanctioner will want to accept a proportion of applicants such that they belong to the good subset A_G in such a way that the ratio of the posterior probabilities of the borrower being a good given that they have a score

[5] The exception to this is the commercial scorecards predicting bankruptcy which is an outcome that can occur years rather than months from the time the scorecard is estimated.

x to the probabilities of the borrower being a bad given that they have the same score x is less than the ratio of loss to the bank through default D to the loss arising through lost profit L. I will explain why this is the case by providing an example. Imagine that the probability, given that the applicant's score is x, that the applicant is good, $P\ (G \mid x\ ) = 97$ percent. Imagine, the corollary to this that the applicant has a 3 percent chance of being bad, given that score x. now the ratio between the two (97/3) is 32. If the cost of a bankruptcy is 32 times the cost of a good misclassified loan, the sanctioner will want to ensure that all loans have at least a 97 percent probability of being good before extending the loan. Otherwise the probability that a loan is misclassified rises and exceeds the tolerance level of 32 set by the bank. This is written in mathematical notation as;

$A_G = \ q\ (G \mid x) \,/\, q(B \mid x) < D/L$

This is the decision rule separating good from bads. The ratio of *D/L*, as we have already indicated, depends on the cost structure of the bank and their tolerance towards default. If the cost of default is very high e.g. with large commercial loans, this ratio will be closer to Altman's estimate of 35/1 for the relative cost of bankruptcy, D, to the opportunity cost, L, of denying funds to a good borrower. In this case the bank will have a lower acceptance rate because it is wary of borrowers who could default. In this case even if the borrower is 4 percent likely to be bad given that he has a certain score but correspondingly 96 percent likely to be a good, the borrower will be rejected.

Table 3.1 shows the decision rule in operation using Altman's *D/L* ratio as a reference point and hence the cut-off point. For ex ante bad likelihoods $q\ (B \mid x)$ of 1-percent and 2-percent, but no higher, the loan sanctioner accepts the loan. However, once the likelihood that an applicant is bad exceeds 2-percent, the loan is rejected. This is because the corresponding ratio between the ex ante good and bad outcomes given the score x i.e. $[q\ (G \mid x) \,/\, q(B \mid x)]$ are only greater than the cut-off of 35 up to this point. If we were to apply the cut-off point that Weiss (1996) advocated of 25 for the costs of misclassifying a bankrupt then the bank would move the cut-off point for $q\ (G \mid x) \,/\, q(B \mid x)$ to 25. With this new cut-off, businesses with a certain score who would exhibit a 3 percent ex ante likelihood of becoming bankrupt would also be accepted. It can be seen therefore, that the less highly the bank rates the cost of the bad outcome against the good outcome *D/L*, the higher the acceptance rate.

I should note here that an individual scoring non-commercial loans might find these cut-off points very conservative. For example, the loss on defaulted credit card repayments or car loan may be considered relatively low against the loss arising when the bank forgoes new business. In fact, a bank may be keen that non-commercial borrowers for financing facilities such as overdrafts actually default occasionally because of the higher interest rates that accrue to the bank on default (Edelman, 1992). Therefore the scorecard should be cognisant of the profit the bank aims to make and not just try to prevent losses arising from the bad outcome, default in this case. It should be clear however, that bankruptcy does not carry any benefit for the bank. Banks will go to great efforts to ward against bankruptcy, sometimes nursing insolvent firms back to health if they perceive that the insolvency is attributable to an event such as an economic downturn rather than managerial or production weaknesses (Wruck, 1990; Lawrence and Arshadi, 1995; Platt et al. 1998). Because of the irreversible and adverse nature of bankruptcy, commercial scoring studies using bankruptcy as an outcome variable tend to have high *D/L* ratios.

Now that I have covered the basic principle of the decision rule, in the next section I describe the process of separation itself.

3.23 Logistic regression as an estimation function

In this section, I outline the logistic regression procedure. I explain the differences between logistic regression and normal regression by referring to Gujarati (1999). Furthermore, I describe the differences in prediction that are obtained when using logistic regression as compared prediction when using the other commonly used algorithm, multiple discriminant analysis, as described by Thomas (1998).

The two most commonly used algorithms for estimating scorecards are multiple discriminant analysis and logistic regression (Hand, 1997; Thomas et al., 2002). According to Hand (1997) there is very little difference in the predictive performance of both. However there are statistical differences between the two that will be explained.

Before the introduction of computers with high computation power, credit scoring favoured the algorithms linear discriminant analysis and linear regression as tools to separate the goods from the bads as opposed to logistic regression. The latter requires relatively more computing power permitting maximum likelihood estimation procedures.

For linear regression, the basis of a good regression is one that minimises sum of errors squared. If the dependent variable is coded $Y=1$ for a default and $Y=0$ for a non-default, then an applicant, i, has his observation coded $y_i = 1$ if he defaulted, or $y_i = 0$ if he was creditworthy. We assume that the bank has collected values for a set of variables or characteristics from his application form and perhaps looked up his credit references for some behavioural information. These explanatory variables that will be used in the subsequent regression for applicant i are $x_{i1}, x_{i2}, x_{i3}....x_{ip}$ if there is p number of variables.

The overall likelihood that the applicant is bad corresponds to the proportion of creditworthy applicants in the population divided by the total number of applicants. In other words, the chance that an applicant is bad is equal to $n_B/(n_B + n_G)$ where n_B is the number of bad applicants and $(n_B + n_B)$ the number of all applicants both good and bad.

The concept of linear regression entails finding weights or coefficients for each of the variables x_{ij}, such that the product of these weights and coefficient values comes close to y_i. In so doing the sum of errors squared is minimised. The objective is therefore to;

Minimise $\Sigma_{i=1}(y_i - \Sigma_j w_j x_{ij})^2$

The coefficients or weights w_j are obtained using the usual ordinary least squares estimators. The Fischer (1936) Linear Disciminant function used in linear discriminant analysis looks very similar. Here the optimal cut-off score x is given as

$$x = \frac{(\mu g - \mu b)}{\lambda S}$$

where λ is a scalar and S is the linear surface separating the mean of the goods μ_g and of the bads μ_b.

Now that I have shown that similarities exist between linear regression and discriminant analysis, I turn to the similarities and differences existing between discriminant analysis and logistic regression. The fundamental similarity between both techniques is their appropriateness for a response variable that is in the binary format (e.g. $y=1$ for a bankrupt firm or $y=1$ otherwise) rather than in a continuous format such as profit levels (Tacq, 1997). Hence, the most striking resemblance between the two techniques is that both techniques are valid for dichotomous outcome variables.

Lo (1986) provides a good mathematical summary of the overlap relationship between logistic regression and discriminant analysis. Let y denote a discrete dichotomous variable that takes the value of 1 for some event such as bankruptcy and 0 for a non-event. Let X be a vector of continuous variables. The joint distribution for y and X is denoted as $F(y, X)$.

According to Lo, an important consideration in choosing between logistic regression and discriminant analysis is the assumption of conditional normality. He argues that it is more convenient to focus on conditional distributions rather than joint distributions when dealing with the classification of cases into groups. This is because the classification of an observation into a group, Y_i, depends on which population that X belongs to. The standard discriminant analysis procedure assumes that the conditional distribution of X with respect to y is multivariate normal with a mean, μ_y, and the common covariance Σ. If $F_D(X \mid y)$ is the conditional distribution, then $f_D(X \mid y)$ is the corresponding density function. However, the logistic function requires no such assumption that the conditional probabilities are multivariate normally distributed. Lo writes the conditional distribution of y with respect to X for the logistic regression as $F_L(y \mid X)$ with $f_L(y \mid X)$ as the corresponding density function.

Discriminant analysis can be related to logistic regression through an application of Baye's Law. Lo begins by taking $F_D(X \mid y)$ denoting the conditional distribution of $X \mid y$ and letting $f_D(X \mid y)$ denote the corresponding density function where, $_D$, denotes discriminant analysis. He states that the;

$$\textit{A priori probability of an event} = \int f_X(X)\, P(y / X)\, dX \qquad \textbf{3.1}$$

We have seen that Lo denotes $F_L(y \mid X)$ as the conditional distribution function of $y \mid X$, where $_L$ denotes logistic regression. By applying Baye's Law and taking on board the different assumptions of logistic regression and discriminant analysis about the distribution of the conditional probabilities, he derives the conditional distribution function of logistic regression in terms of the conditional distribution function of discriminant analysis as;

$$F_L(y \mid X) = [\, f_D(X \mid y) * \textit{A priori probability of an event}\,] / f_X(X) \qquad \textbf{3.2}$$

The problem with linear discriminant analysis, as we have seen, that is addressed by logistic regression is that linear discriminant analysis assumes that the conditional distribution of X with respect to y is multivariate normal. In other words, discriminant analysis assumes that the covariance matrix X_{ij} is the same for the population of goods and bads (Eisenbeis, 1978). According to Thomas (1998), this is an unreasonable assumption to make. If one were to assume unequal covariance matrices between the goods and the bads, one would need to use a quadratic formulation of the linear discriminant function and this would greatly increase the number of explanatory variables to be computed.

Although logistic regression got around the problem of assuming equal covariances matrices, due to the different way it is formulated, it was never really regarded as a real substitute for linear disciminant analysis until the advent of powerful computers made scorecards using linear regression relatively easy to compute.

The way logistic regression avoids the problems of covariance equality between the defaulters and non-defaulters is not just confined to its different specification that I will describe. It is also because an assumption of equal covariances is unnecessary for the estimation of the parameters. Regarding its specification, instead of assuming that the probability of being a bad p_i is equal to the sum of the product of the variables for each applicant x_{ij} by their respective variable coefficient w_j as follows;

$p_i = w_0 + w_1x_{i1} + w_2x_{i2} + w_3x_{i3} + w_4x_{i4} + \ldots.. w_px_{ip}$

Logistic regression assumes that the *log of the odds* of being a defaulter (unlike linear regression that assumes the probability of being a defaulter) is equal to the sum of the product of the variables for each applicant x_{ij} by their respective variable coefficient w_j. The odds of being a defaulter are equal to the probability of being a defaulter divided by the probability the person is not a defaulter. In other words, if the probability that an applicant is a defaulter is p, the odds of him being a defaulter are $p /(1 - p)$. The formula for logistic regression is therefore;

$log(p_i/1 - p_i)= w_0 + w_1x_{i1} + w_2x_{i2} + w_3x_{i3} + w_4x_{i4} + \ldots.. w_jx_{ij}$

The advantage of logistic regression is that it does not require the assumption that the covariance matrices of the defaulters and non-defaulters are equal. Also, if any of the explanatory variables are dummy variables (categorical variables in this particular instance constructed from continuous variables), the expression is still robust to any changes in the distributions these different formats of the explanatory variables bring about.

A further advantage of logistic regression, this time compared with normal linear regression, is that it constrains the probability of being a default within the range 0 to 1 (Gujarati, 1999). With normal linear regression, there is no guarantee that the estimated probability of the borrower being a bad will fall between 0 and 1. If an estimated probability is negative or greater than 0, it is meaningless. The use of logistic regression avoids the possibility that the probability will lie outside the acceptable range of probabilities. The logistic regression schedule is described by an S-shaped curve (**Figure 3.1**).

You can see from **Figure 3.1** that logistic regression performs much the same way as ordinary linear regression for most of its range where the function describing the logistic regression tracks the linear function and only is non-linear at its extremes. You can see that it is bounded between 0 and 1 on the y-axis. This means that the levels of the response variable lie on either horizontal line where $y=0$ (representing non-default) or $y=1$ (representing default).

Following the introduction of high-powered computers the maximum likelihood technique used to estimate logistic regression is now feasible and easy to apply. According to Thomas (1998), logistic regression is the technique most preferred by credit scoring practitioners.

Logistic regression is also used in several of the commercial credit scoring studies that I will describe later (Leonard, 1992; Wiginton, 1980; Ohlson, 1980; Platt and Platt, 1987; Platt and Platt, 1991b). There is therefore a well established precedent for my analysis in

Chapter 6 using logistic regression since it has been used by both practitioners and academic researchers before.

We have defined what the logistic regression algorithm is and have compared it with the main other statistical technique used in scorecards linear discriminant analysis. I now demonstrate how logistic regression is applied and interpreted using an example and outline the corresponding goodness of fit statistics used in logistic models.

Let us assume that we have two explanatory variables x_1 and x_2 where x_1 represents business gross profit from the previous year's operations and x_2 the sales turnover from the current year.

The odds ratio of borrowers defaulting on their loans is $(P_B /(1- P_B))$ where P_B denotes the probability of default occurring within 6-months and $1 - P_B$ the probability that it does not occur. Taking the natural log of the odds ratio and equating this with two hypothetical scorecard variables, by way of example, gives the following model with the error term e_i;

$ln(P_i /(1 - P_i)) = \beta_0 + \beta_1(Gross\ Profit\ level\ from\ Year_{t-1})_i + \beta_2\ (sales\ turnover\ from\ Year_t)_i + e_i$

The log of the odds ratio $ln(P_i/(1 - P_i))$ is a linear function of the explanatory variables last year's gross profit level and this year's sales turnover. The predicted value of the dependent variable if the borrower has gross profit of £40,000 and sales turnover of £120,000 is -3.6007. That is;

$ln(P_B /(1 - P_B)) = -3.6007$

This is then antilogged to give e raised to the power of -3.6007.

$(P_i /(1 - Pi)) = e^{-3.6007}$

reorganising gives

$P_i = (e^{-3.6007})/(1 + e^{-3.6007})$

This gives a value of 0.0266. In other words, a hypothetical business with a gross profit level of £40,000 and sales turnover of £120,000 can be expected to be approximately 3 percent likely to show default on its borrowing 6 months later. In general, the higher the value of the logit, the higher the corresponding odds of the event occurring are and therefore the higher the likelihood of the event occurring.

The discussion now turns to the goodness of fit statistics used in logistic regression, comparing them with their corresponding test statistics in OLS regression.

In ordinary linear regression, the aim of the model is to minimise the *SSE* (Sum of Errors Squared) or unexplained variance as a proportion of overall variance *SSR* (Sum of the Errors Squared explained by the Regression). The F test in linear regression tests the null hypothesis that all the co-efficients are equal to zero *(H0:* $\beta_1 = \beta_2 = \beta_3 ... = \beta_k = 0$*)* where F is defined as

[SSR/k] / [SSE/(N-k-1)], N is the number of observations in the sample and k the number of explanatory variables.

The parallel to the F test in logistic regression is the log-likelihood. The initial log likelihood function is analogous to *SST* (Total Sum of Squares) in OLS regression. This is referred to in notation by Menard (1995) as D_0, or the chi-squared value for the intercept only. The deviation for the full model (analogous to *SSE*) is D_M. When this deviation value for the model (D_M) is subtracted from D_0, G_M is obtained which indicates the variance explained by the model, analogous to *SSR* in OLS regression. The significance level of the variance explained by the model, G_M , is equivalent to the F test in OLS.

The *pseudo* R^2L for logistic regression and which is the most natural parallel to *SSR/SST* and indicates the goodness of fit for the regression is

$R^2L = (D_0 - D_M)/D_0$

In this section the justifications for using the logit model were presented. The way the logit model operates was illustrated and explained using a hypothetical credit scoring scenario with two explanatory variables. Finally, statistics used to evaluate the power of logit regression models were presented alongside their parallel statistics in OLS.

The following section describes a technique less well known than the logistic regression algorithm I will take care to explain the weights of evidence method used in the preparation of the explanatory variables for the logistic regression model because of its lack of broad application outside the area of credit scoring.

3.24 Selection and preparation of the right hand side variables

This section deals specifically with the preparation and selection of the explanatory variables. Dealing firstly with the preparation of the explanatory variables. A common problem in the construction of a scorecard is the limited number of observations in the estimation sample compared with the abundance of explanatory variables. This reduces the statistical power of the resulting model. This problem is compounded when the continuous variables such as entrepreneur's age are transformed into categorical dummy variables. Hence age can be reduced to the categorical classes age 18-25, 26-35, 36-45, 45-65 and 65+ depending on the number of observations in each category. Also a researcher could apply some a priori reasoning for the definition of ranges of values to categorical variables. An example of this would be where he could inform his decision based on government statistics on the age at which self-employment becomes more a more lucrative alternative to waged employment. Alternatively, the age at which waged, blue-collar employees, in the event of redundancy from their job, are unable to re-enter the labour market because they are too old to be retrained (the economic theory describing employment push factors be applied in this case)[6].

A difficulty arises where the number of variables is increased considerably with the addition of extra categories. This problem is discussed by Crook, Hamilton and Thomas (1992b). A way they suggest getting around the problem caused by a reduction in degrees of freedom is to construct 'weights of evidence' for continuous and dummy variables alike. Thomas (1998) also refers to this often used technique as a way of overcoming the problems where there are a large number of right hand side variables.

Thomas (1998) suggests that there are three ways of organising categorical right hand side variables. The most intuitive would be use *n-1* dummy binary variables to represent n number of categories as described above. He argues that the advantage of this technique is that it does not impose any relationship on the coefficients of the variables. A disadvantage is that it leads to a large number of variables with losses of degrees of freedom.

The second method is the location model where a different discriminant function with the continuous variables is estimated for every combination of categories of the categorical variables. This has the disadvantage of being difficult to apply because of the large number of discriminant functions.

The third method is the one referred to by practitioners, according to Thomas (1998). According to Thomas, a valuable feature of the weights of evidence method is that it can allow quick updates of the existing data to incorporate new data. It is also used by some other researchers (Banasik et al., 2001; Banasik et al., 1996; Crook et al., 1992b; Wiginton, 1980).

The weights of evidence method deals with non-linearities in the data by grouping both categorical as well as numerical variables into homogenous groups or intervals and finding the log of the proportion of the total number of goods to the proportion of the total number of bads for that category within a characteristic, such as Marital Status. In the case of continuous variables, an example being an entrepreneur's age, several groups can be chosen. This gives a step function rather than smooth continuous function for age (**Figure 3.2**).The weights of evidence values are calculated as:

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[6] Purely predictive scorecards do not have to take economic theory into consideration when informing their choice of categorical variable categories. The issue is <u>whether</u> a variable proved to be predictive rather than <u>why</u> the variable was predictive

$$X_z = \ln \frac{g_i}{b_i} + \ln \frac{B_T}{G_T}$$

where X_z = value of predictor X for category z

g_i = number of good payers in nominal category z, the category of which the i is a member

b_i = number of poor payers in nominal category z, the category of which i is a member

G_T = number of good payers in the sample responding to this question

B_T = number of poor payers in the sample responding to this question

Essentially, the replies to different questions on the loan application forms can be processed in this way where each question represents a category and each reply or response represents an attribute. B_T and G_T represent the frequencies of goods and bads answering this question. The more interesting piece of information is the frequency of goods g_i and bads b_i for each of the attributes because it can happen, for example, that Divorcees exhibit relatively higher default rates than the Widowed. In this case the proportions of each will capture the higher propensity of Divorcees to default.

Now that we have looked at the preparation of the explanatory variables, how does the application scorecard builder select the variables for inclusion in his scorecard estimations? In practice, any variable that proves to be significant is retained in a credit-scoring model. Consistent with the aim of scorecard construction to choose the most discriminative (able to discriminate between good and bad outcomes) as opposed to the most theoretically valid, the most popular methods of choosing the explanatory variables comprise the stepwise or forward inclusion method or the backward deletion method.

Gujarati (1992) explains how these techniques allow for the exclusion of variables that are *'probably superfluous'*, leading to clearer models. He uses the word *'probably'* because if there is collinearity among the explanatory variables, the standard errors tend to be higher and the estimated t-values are reduced(*t= beta/standard error beta*). Because of the reduction in the t-values with collinearity, it is more difficult to reject the null hypothesis that the variable explains the response variable i.e. is meaningful and hence exclude the variable from the model on the grounds that it is probably superfluous. Gujarati being a writer steeped in the economic tradition, condemns data mining approaches where the variables are all selected in this way and the researcher does not set out with a model in mind.

Some of the academic literature dealing with commercial scoring has criticised this heuristic approach to variable selection. Pinches, Mingo and Carruthers (1973) employed factor analysis in their selection of variables in an attempt to isolate factors representing variables with high commonalties. Factors such as cash flow or liquidity measures correspond with financial theory and provide the necessary reference points for an interpretation of the outcomes.

Following on the lead established by Pinches, Mingo and Carruthers (1973), commercial scoring studies by Barnes (1987) and Zavgren (1985) also employed factor analyses in their variable selection procedures.

Finally, it may seem that the selection of explanatory variables based on their F statistic as employed in stepwise, forward or backward selection methods may be expected to affect comparability among different scorecards adversely and possibly different predictive performance.

However, Lovie and Lovie (1986) first discovered that the eventual predictive power of a scorecard is relatively insensitive to the precise values of the coefficients of the explanatory variables. This is known as the *flat maximum effect*. The flat maximum effect is of no use to a researcher wanting to interpret the coefficients of a scorecard and discuss their individual power. However, it is a bonus for researchers who are interested in the pure predictive power of the models. The flat maximum effect has made it possible to create 'generic scorecards' that can be applied on different datasets. Overstreet and Bradley (1992), in an analysis of consumer credit created a generic scorecard using data from US credit unions. They concluded that customised models perform better than generic models at classifying the bad outcomes (reduce Type I error) However they would not be as robust where credit unions widen their customer base as they are modelled on a very narrow set of clients. The flat maximum effect exhibited by generic models reduces the marginal level of misclassifying good loans compared with customised models.

3.25 Distinguishing a good from a bad scorecard

The next issue deals with scorecard discrimination. Since the science or art of credit scoring emphasises the separation of creditworthy from non-creditworthy firms, it follows that a good scorecard should be able to discriminate between both types of applicant.

The separation between goods and bads in the following way. **Figure 3.3** taken from Hanley (2000) shows the separation of bads and goods in a consumer credit scorecard. The posterior probabilities that the consumer is a bad are described by the *x*-axis. The frequency of creditworthy and non-creditworthy customers is indicated by the *y*-axis. The type of non-creditworthy behaviour measured by the response variable in this example is whether the applicant missed at least 2 consecutive repayments on their repayment schedule. The distribution of applicants missing at least 2 consecutive repayments (dark-shaded distribution) lies slightly more to the right than the distribution of applicants who never exhibited this type of adverse repayment behaviour. This is because at higher predicted probabilities that an applicant is bad, we would expect a comparatively high frequency of bads relative to goods. The corollary to this is that at low predicted probabilities that applicants turn out to be non-creditworthy, we would expect a comparatively low frequency of non-creditworthy compared to creditworthy applicants. Therefore, although there are higher numbers of creditworthy applicants overall, we can observe a slight bias towards the right (higher expected probabilities of an applicant being bad) for the applicants missing at least 2 consecutive repayments.

If the distribution of the applicants missing at least 2 consecutive repayments on their borrowings lies far to the right and there is no overlap, we can conclude that the scorecard offered complete separation of the goods from the bads in the estimation sample. Such a highly discriminative scorecard would be useful to the bank because they would be extremely confident that applicants exhibiting certain characteristics would turn out to be bad based on the previous association between these characteristics and the bad outcome.

Many scorecards do not permit full separation of the creditworthy from non-creditworthy borrowers and some overlap exists between the two distributions. In practice, a bank may review these marginal applicants who fall in the overlap area in more detail. A sanctioner may request more comprehensive credit bureau data for these cases. Where there is no overlap, the bank is more confident of correctly predicting the repayment behaviour of the applicant and will reject applicants at the extreme values of posterior probabilities. Therefore a scorecard with overlap can still save the bank time and money by dispensing with the need to scrutinise applicants at the extremes of the distributions and instead focus on the marginal cases where the repayment outcome is more uncertain.

A bank, when assessing the ability of a scorecard to discriminate between the goods and bads, can employ two main techniques in order to evaluate the scorecard; classification matrices and gini coefficients. I will now describe these techniques and relate them back to **Figure 3.3** before turning to a more detailed description.

The first and most basic way to evaluate the power of a scorecard is to derive a classification matrix referred to as a *'confusion matrix'* (Hand, 1997).

Looking back at **Figure 3.3**, a classification matrix is a 2 by 2 matrix that presents a snapshot of how well the scorecard has performed at a particular expected probability level. We see how the classification operates in the small classification matrix below (See **Table**

3.2). The error rates correspond to the proportion of events incorrectly predicted for each of the outcomes as a proportion of all applicants showing that outcome. The proportion or rate correctly predicted bad is $a/(a + c)$ or the number correctly predicted to be bad divided by the total number of bads. The proportion or rate correctly predicted to be good corresponds to $d/(b + d)$. If we are trying to predict the bad outcome (response variable $y=1$ for a bad outcome) then $a/(a + c)$ is also referred to as the true positive rate and $d/(b + d)$ as the true negative rate.

Table 3.2 ***'Confusion'* matrix**

		Predicted class (# of cases)		
		Ever bad	**Never bad**	**Total**
True class (# of cases)	Ever bad	a	c	$a+c$
	Never bad	b	d	$b+d$

The classification matrix provides a useful method of evaluating the trade-off between the correct prediction of an event (applicant is non-creditworthy) and the correct prediction of a non-event (applicant is creditworthy). The percentages of goods and bads correctly classified are dependent on the cut-off used. Imagine that the behaviour we are attempting to predict is whether or not the customer defaults on his repayments i.e. P_B. If we start off by assuming the default cut-off of 0.50, we may find that only a few of the bads are correctly classified. If there is a low number of bads in the estimation sample, it may be more difficult for the scorecard to detect them. This is because all things equal, an observation randomly selected from the sample is most likely to be a good due to the higher relative frequency of goods in the sample. If we however raise the cut-off from 0.5 to 0.6 in order that we have a higher likelihood of detecting good applicants (where the response variable is coded as 1 to denote a good), then we should find that the classification accuracy for goods should improve but at the expense of misclassifying a higher proportion of the bads. In other words, the true positive rate $d / (b + d)$ will increase and the true negative rate $a / (a + c)$ will decrease. Conversely, if we lower the cut-off rate, the classification accuracy of the bads improves at the expense of the goods. It follows that the true negative rate $a / (a + c)$ will increase and the true positive rate $d / (b + d)$ will decrease.

It is important to note when using true positive and negative rates that they are aligned to whatever is deemed to be 'an event' by the statistician. In other words, an event can be either taken to mean the detection of a bad observation or alternatively of a good observation. As long as the statistician indicates what he means as an event, we can interpret the true error rates accordingly. For example, if the statistician deemed the detection of a bankruptcy or default as an event, then the true positive rate would now imply the detection (prediction) of bad observations as a percentage of all bad observations in the estimation sample i.e. $a / (a + c)$[7]. Similarly, the true negative rate would now be switched to imply the correct prediction of all good observations as a percentage of all good observations i.e. $d / (b + d)$.

Apart from being aware of what represents 'an event' and the implications of how the response variable is coded for the interpretation of the true error rates, there are other issues that are worth noting in the context of cut-off rates. One way of determining the cut-off point is to set it at such a level that the actual number of bads (assuming that bad observations are events) is equal to the predicted number of bads. In other words, there is full classification accuracy of the bads. Now the researcher ascertains the proportion of goods correctly classified (true negative rate) at this pre-determined cut-off where all bads have been correctly classified. This approach of fixing the cut-off at a level where the predicted number of bads equals the actual number of bads was employed by Banasik et al. (1996) when they experimented with various different types of cut-off.

One of the problems with the classification matrix is that it can only report the breakdown in predictions for one expected probability level. For example, it might report the breakdown of goods and bads at an expected probability level of 0.50 that the applicant is non-creditworthy. In order to address the performance of the scorecard over the whole range of the probability levels, the gini coefficient can be used. This is also referred to in Hand (1997) as the Wilcoxon-Mann-Whitney test.

The most powerful measure of separation between the two distributions is the Wilcoxon-Mann-Whitney test (Hand, 1997; SAS Institute, 1999). The Wilcoxon-Mann-Whitney test is also equivalent to the area under the ROC curve or the gini coefficient (Hand, 1997). ROC curves are useful because it is necessary to calculate global discriminatory power over all the cut-offs instead of the discriminatory power at one single cut-off. In other words, ROC curves give a more comprehensive view of the performance of the scorecard over all the

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[7] Bankruptcy or default are typically coded as 1 in credit scoring scenarios because the lender is more interested in reducing the costs of lending to firms who subsequently default rather than minimising the cost of withholding finance from a borrower who turns out to be good. However, the codification of the response variable depends on the relative costs the bank places on both types of misclassification error.

expected probability levels unlike the classification matrix reporting the performance at a particular expected probability level.

Figure 3.4 illustrates what a ROC curve looks like. Sensitivity or the true positive rate $a/(a + c)$ is described by the y-axis. 1 minus specificity, or one minus the true negative rate, $d/(b + d)$ is depicted on the x-axis.

In **Figure 3.3** you can see that the curve is crescent shaped and is described by the co-ordinates (0,0) and (1,1) at either extreme. A 45 degree line intersects it at its extremes.

A good scorecard should describe an arc capturing as large an area as possible between itself and the 45 degree line. If the scorecard were perfectly predictive, as we described earlier in the case of perfect separation of creditworthy from non-creditworthy borrowers, the schedule would be coincident with the y-axis and form a triangle with the 45 degree line. This would happen because the scorecard would perfectly distinguish all bads without misclassifying any goods in the process. In other words, the true negative rate, $a / a + c)$, would be equal to 1 and the true positive rate, $d / (b + d)$, would also be equal to 1, yielding a specificity (1 – true positive rate) of zero. Hence the co-ordinates (0,1) would be on a perfectly discriminatory scorecard.

A scorecard with no discrimination would be described by a ROC curve coincident with the 45° line. This is because in order to correctly classify some observations as events, a corresponding number of non-events would have to be misclassified. The true positive and true negative rates would be perfectly correlated with no discrimination because classification would depend on the frequency of events and non-events in the estimation sample and hence there would be a direct correspondence between classification and misclassification. For example, imagine that there were 50 events and 50 non-events. With a perfectly non-discriminatory scorecard, I could correctly predict 40 events only at the expense of misclassifying 40 non-events. This would give true positive and true negative rates of 0.8. I could correctly 30 events at the cost of misclassifying 30 non-events yielding true positive and true negative rates of 0.6. Since the positive and negative error rates are equal in each instance, a straight line can be plotted from the origin to the co-ordinate (1,1) describing a 45° line.

The gini coefficient summarises the ROC curve by reporting the area under the ROC curve[8]. Their procedure is based on the ranks of the data. The predicted posterior probabilities are

[8] SAS software applies a procedure called *'Wilcoxon'* to produce the output from which the gini coefficient can be calculated.

ranked from smallest to largest. The area under the ROC curve *c*, can be determined from the rank-sum in the class where $y=1$ (an event occurs such as default).

$$c = \sum_{(i|y=1)}^{ni} [\ R_i - 1/2n_1(n_1+1)\ ]/(n_1 * n_0)$$

where R_i is the sum of scores for the bads, *c* is the area under the ROC curve or gini, n_o is the number of goods and finally n_1 is the number of bads.

Classification matrices and ROC curves deal with the accuracy of the scorecard. However, this accuracy is upwardly biased if the classifier function is applied to the sample that the scorecard was estimated on. The error rate is referred to as the '*apparent error*' rate because of this bias.

There are several ways of dealing with this bias all of which, to some extent, involve estimating the scorecard on a subset of the data and testing the classifier function on the remaining observations to see if they are accurately classified.

The first method of ex ante validation of the scorecard classifier that is used in commercial credit scoring is the leave-out-one method (Betts and Belhoul, 1987; Platt and Platt, 1992). This method developed by Lachenbruch (1975) estimates the classifier function on all but one of the points and allows the scorecard to classifying the remaining observation. This is repeated for all the observations in the sample. There is little bias using this method. Thomas (1998) notes that its disadvantage is the large variance.

The second method is the bootstrap method which is used in commercial scoring analyses by Taffler (1982) and Srinivasan and Kim (1987).The bootstrap can be used effectively for small samples like Taffler's who had only 68 observations or Srinivasan and Kim's which had 215 observations of which 39 were high risk.

The bootstrap is a bit more complicated than the leave-out-one method. It assumes that, if e_T is the true error rate, e_A the apparent rate and *b* is the expected optimism or bias of the apparent error rate, then the true error rate e_T can be expressed as $e_T = e_A + b$. The expected optimism, *b,* is estimated by drawing random samples with replacement S^* from the original sample *S* to build a classifying function. The classification error on S* is compared with the error obtained on *S* and the difference is taken as an estimate of *b*. This procedure is repeated for different samples S^* and estimates *b* are obtained, which in turn, provide an estimate of the true error rate e_T.

The holdout sample method is another common method used in credit scoring studies of checking the ex ante validity of the scorecard. This is a version of the leave-out-one method. However, instead of classifying on the one remaining observation, it divides the sample into two large subsets (estimation and holdout sample) and tests the classifier on the subset that was not used to estimate the classifier. This technique was used by Schellenger and Cross (1994). They took 2,345 businesses and divided it such that the estimation sample contained 1,545 non-bankrupt businesses and 45 bankrupts (roughly 68 percent of the entire dataset). They then tested the classifier on the remaining 735 non-bankrupts and 20 bankrupts.

An ex ante classification method that is not mentioned by Thomas (1998) but is used in commercial credit scoring is to try the classifier on entirely new data. This is the purest test of a classifier because it is not contaminated by any bias whatsoever. Zavgren (1985) applies her classifier to an unseen sample of firms on the New York Stock Exchange, some of whom had gone bankrupt. Platt and Platt (1992) also test their classifier on unseen business data.

A feature of some bankruptcy prediction models is that they tend to be a bit more lax about ex ante classification than credit scoring models in the consumer credit literature. This tendency is criticised by Zavgren (1985). Hence bankruptcy prediction analyses by Weiss (1996) and Piesse and Wood (1992) do not apply ex ante classification techniques. Weiss is more concerned with being able to 'predict' bankruptcy 1 or 5 years from the event and the impact of the bank's trade-off ratio D/L described in section **3.22** earlier. Piesse and Wood (1992) are more concerned with the supposed accuracy in commercial scoring where accuracy is illusory because it is inflated when the estimation samples are biased towards picking winning or losing firms at both extremes of the financial health scale. Business scorecards predict comparatively well when the event denoted by the response variable is complete failure rather than financial distress. There is more polarisation between bankrupt and good firms than between financially distressed surviving firms and good firms. If surviving but financially distressed firms are included, their failure (bankruptcy) is predicted despite the fact that they remain in existence. Therefore, more representative estimation samples would commit a lot of Type II error where surviving businesses would be flagged as bankrupts.

Neither of these two analyses performs ex ante validation and yet they are often cited. It therefore appears that while proper ex ante validation is deemed a good thing by writers such as Zavgren (1985), ex ante validation is not as highly emphasised by researchers in the area of bankruptcy prediction than researchers in the area of commercial scoring. One possible reason for this lack of emphasis on determining how robust a bankruptcy prediction model is when tested on a hold out sample, is that the number of observations is so low that performing a split such as 40/60 is not a realistic option. This would mean reducing the estimation sample by 60 percent. However, notwithstanding the fact that bankruptcy studies typically have less data available to them then commercial scoring studies, it is suprising that leave-out-one or bootstrapping methods, which can be used in the case of small samples, are not more prevalent. The prediction of bankruptcy is a useful piece of information in a bankruptcy analysis but I dispute that bankruptcy studies are aimed at practitioners with the aim of commercialising their work but rather on shedding insights on what induces business failure[9].

3.3 Conclusion

I have introduced and described the standard credit scoring procedures and the methods for evaluating the effectiveness of scorecards. These sections should help to clarify the approach I will use to estimate my own small business scorecard in **Chapter 6**. I have indicated that logistic regression rather than linear discriminant analysis is regarded as the industry standard (Thomas, 1998). It also avoids possible problems that could arise if the covariance matrices of the good and bad firms are not similar. In reality, previous analyses have shown that there is little difference between the two estimation procedures in terms of results (Leonard; 1992; Srinivasan and Kim, 1987; Hamer, 1983).

A researcher wishing to organise the explanatory variables in a small business scorecard can apply the weights of evidence procedures used by Crook, Hamilton and Thomas (1992b) and described by Thomas (1998). This procedure provides an alternative to constructing categorical dummy variables which would raise the number of right hand side variables considerably causing losses in the degrees of freedom of the scorecard estimation regression.

I have described the methods of evaluating scorecards and emphasised the importance of ex ante or out-of-sample validation. Classification matrices can be used to evaluate the discriminatory power of my scorecard for one cut-off. A researcher wishing to evaluate a scorecard over all possible cut-offs, can refer to the gini coefficient and graphical ROC curve.

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[9] The exception to the lack of applicability of bankruptcy studies to real life business scoring are studies by Altman who has developed and commercialised the z score. However, in general bankruptcy studies tend to be academic rather than applied

Figure 3.1 Format of the logistic function

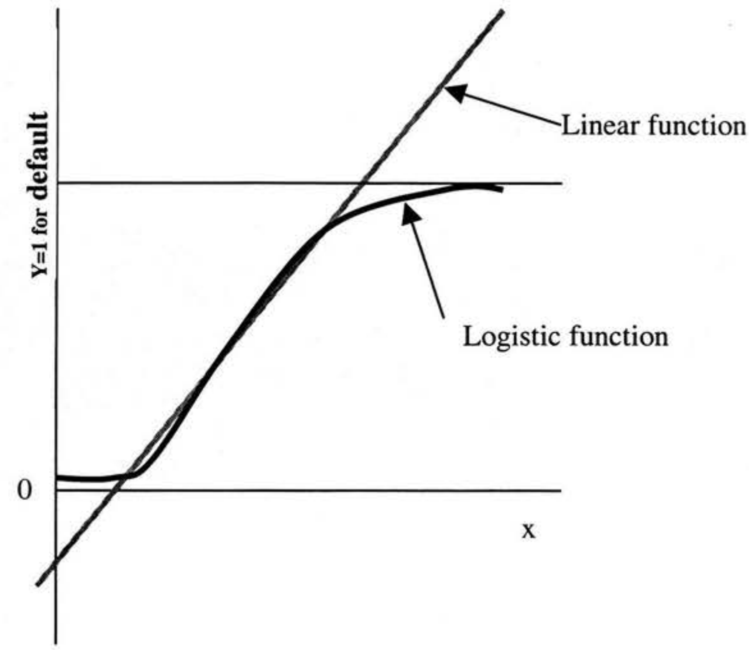

Figure 3.2 Classification under weights of evidence method

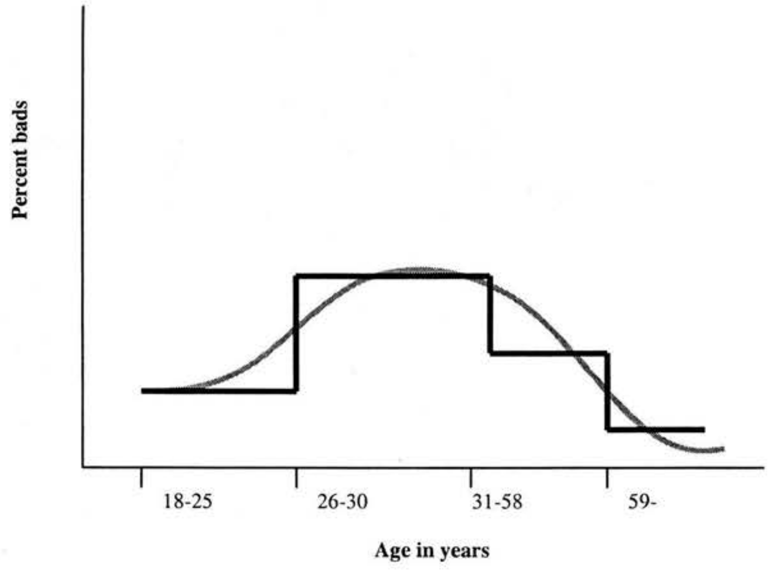

Figure 3.3 Scorecard separation of creditworthy from non-creditworthy customers

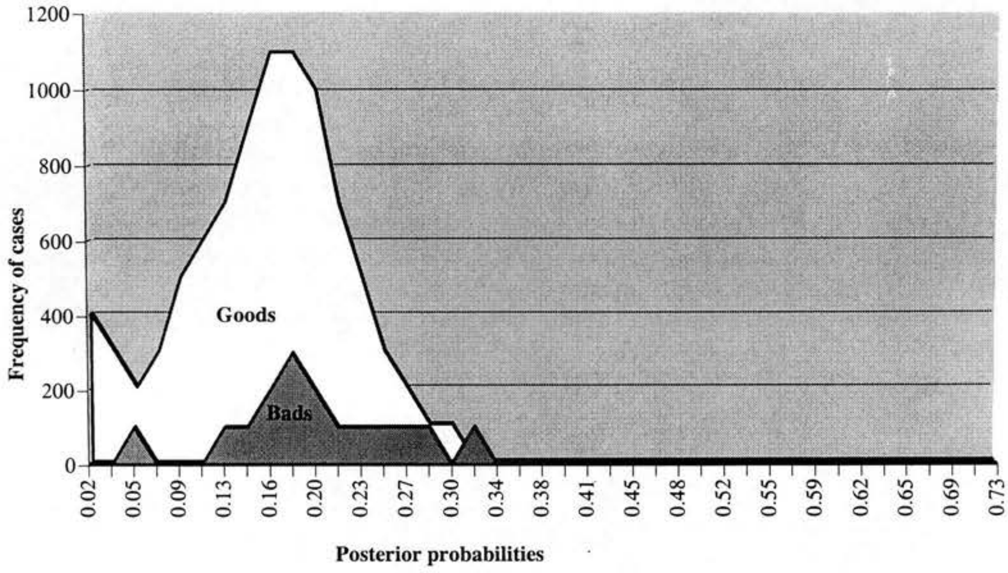

Figure 3.4 Diagram of ROC curve

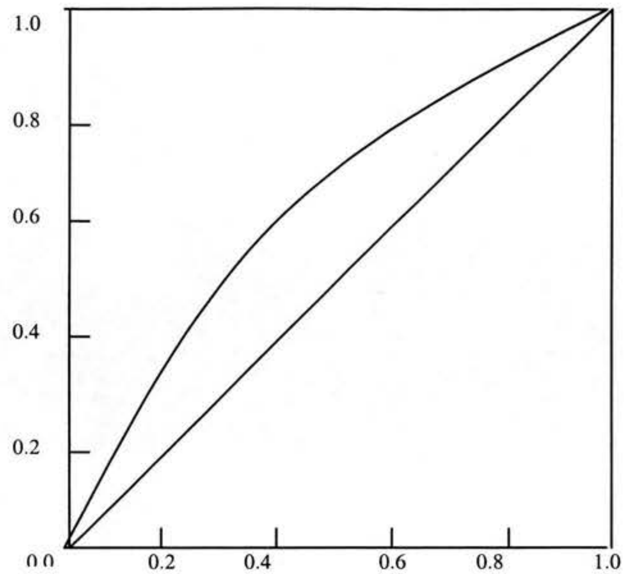

Table 3.1	Decision rule using Altman's 1977 D/L ratio			
Acceptance region	$q(B \mid x)$	$q(G \mid x)$	$q(G \mid x) / q(B \mid x)$	Cut-off
	1	99	99.00	35
	2	98	49.00	
	3	97	32.33	
	4	96	24.00	
	5	95	19.00	
	6	94	15.67	
	7	93	13.29	
	8	92	11.50	
	9	91	10.11	
	10	90	9.00	
	11	89	8.09	
	12	88	7.33	
	13	87	6.69	
	14	86	6.14	
	15	85	5.67	

Chapter Four

The issues in scoring businesses

4.1 Review of gaps in the commercial scoring literature

The aim of this chapter is to present the gap in the literature that my analysis in **Chapter 6** attempts to fill. In establishing that gaps exist in the literature, I refer to what existing studies have already achieved and how no published study to date has provided an adequate example of a small business application scorecard.

Part of the reason for this literature gap is that while small business application scorecards exist, their performance and composition remains secret. The most prominent US small business scorecard is the Fair Isaac model pioneered recently, as described by Asch (1995) and Mester (1997). I have already highlighted in the previous chapter, that banks or scoring institutions do not divulge their scoring practices. Hand (1997) argues that;

'..credit scoring is a commercially sensitive application. Banks are not in the business of publishing scientific papers which would reveal the basis of any commercial edge they may have gained'[1].

Crook et al. (1992), on the other hand argue, that the flow of information about credit scoring derives from practitioners rather than academic researchers and they can point to more work from practitioners in this area;

'Research into credit scoring is almost exclusively the province of the practitioners who develop and use credit scoring systems, but such research must be short term and geared to new product development. Academic researchers into the topics are few and far between'[2].

These two views by Crook et al. (1992) and Hand (1997) point to a paucity in the academic literature. Where practitioners contribute to the literature, their papers are wary of disclosing any information that would confer an advantage to competing banks or credit scoring agencies. In an industry where every percentage point in improvement can increase bank profits considerably, this reticence on the part of practitioners is understandable. Nonetheless, it opens up the way for more academic literature to make good any shortfalls in our understanding of small business scoring.

However, some analysts may argue that businesses have been scored and therefore it is likely that they would deny a literature gap exists. I will go on to demonstrate that business delinquency has been estimated before and that there is a plethora of studies estimating business delinquency in different forms. However, these existing studies attempt to predict that a large, listed business turns bankrupt. This type of analysis, which is referred to as a Z-score analysis and which is described later, is inappropriate for the scoring of small

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[1] P.174 Hand, 1997

[2] From Preface, P.i Crook et al. (1992). 'Credit Scoring and Credit Control'.

businesses. It should become clear in the course of this chapter that bankruptcy studies, of which the Z-score analysis is the first formalised bankruptcy study since its inception in the 1980's, relies on timely and accurate accountancy data in order to predict bankruptcy. Small firms do not have to provide audited accounts (Gower, 1992). If non-audited accounts are used, there is a suspicion that an entrepreneur can manipulate them (Zavgren, 1985). Finally, there is the argument that human capital variables such as age and work experience should be used in a small business scorecard. Cressy (1996a) has demonstrated that these variables are highly correlated with the survival of a small firm. However, no Zeta score analysis includes human capital variables in its default estimation, possibly because as firms become larger and the ownership structure more dispersed, the relationship between the human capital variables of the firm's founder and eventual default may become more tenuous.

It should be clear therefore, that while the Zeta analysis is potentially useful for the prediction of default in large businesses, where bankruptcy proxies delinquency, that it is inappropriate for the scoring of small businesses. This is precisely the gap in the literature that needs to be addressed by an analysis estimating a small business scorecard.

A further gap in the literature arises from the predominance of bankruptcy as a measure of default. A bank may be more interested in predicting distress rather than bankruptcy since the former is a more frequent event (distress is a precursor to bankruptcy) and yet by the time bankruptcy arises, it is already too late for a bank to consider taking any action. By the time a business has been declared a bankrupt, it is likely that the bank has already had to incur considerable expense in attempting to recoup its investment. Some banks may reschedule debts and reorganise the business, as indicated by Wruck (1990). Therefore, a measure of default that occurs prior to bankruptcy and that is indicative of financial distress, is of more use to a bank because it is more timely. The time for bank action is the event horizon prior to bankruptcy and therefore a bank requires an early warning system. However, financial distress is an outcome that is more difficult to predict than bankruptcy because the symptoms are not as pronounced (Gilbert et al., 1990; Altman et. al., 1994).

To date, one direct analysis has been carried out to deriving a scorecard for commercial loans using credit grade, indicative of financial distress, rather than bankruptcy as the response variable (Dietrich and Kaplan, 1982). The fact that serious commercial default represents a potentially useful outcome variable but that studies of commercial default/distress are dominated by studies estimating bankruptcy, provides a further motivation for my research.

This next section outlines the differences between commercial and non-commercial credit scoring. The section following this compares and contrasts the dominant type of commercial scorecard, called the Zeta scorecard, pioneered by Altman and discusses whether it is applicable to small business scoring. The section following this deals with the type of outcome variables used in previous commercial scoring analyses and highlights some controversies in this area. I conclude with a summary of the gaps in the commercial scoring literature.

4.2 Distinction between commercial and mainstream credit scoring

The literature on the scoring of consumers for credit products is data driven and very much influenced by what method works best and the rigour of cross-validation. However, the commercial scoring literature which represents the subject of this chapter, while not theoretical in that no financial economic models are presented, is to a large extent interpretative. This is because the derivation of the explanatory variables, for models such as the Zeta model, is based on the use of established financial indicators that have informed decision-makers prior to the advent of scorecards. The fusion of accountancy and prediction means that researchers commonly attempt to interpret their results by referring to the established rules on the interpretation of accounting ratios and variables. Past critics of the system include Barnes (1987) who criticises the lack of a theoretical underpinning in bankruptcy studies as follows;

'..*as company failure studies blatantly demonstrate, accounting ratios are rarely used in the financial literature to test theories and hypotheses of economic and financial behaviour*'[3].

Altman et al. (1994) have also commented on the lack of a theoretical underpinning for bankruptcy models. They do not condemn the lack of a theoretical background but argue that data driven techniques are quite appropriate;

'*We know many things about how companies can fall into economic distress, about crisis procedures and company decline, but we do not have a complete theory*'[4].

This lack of theoretical literature underpinning the derivation of commercial scorecards contrasts with the theory-rich **Chapter 2**, where the issues investigated deal with the nature of small business loans.

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[3] Barnes, 1987. P.457

4.3 Bankruptcy prediction (Zeta analysis) and the prediction of SME default

In this section, I introduce the main type of business scorecard, the Zeta scorecard used for predicting bankruptcy, and discuss whether it is relevant for the scoring of small businesses. I look into several issues surrounding zeta type analyses before concluding whether they are applicable to small business scoring. Moreover, I discuss matched sample design, the reliability of accounting ratios and the availability and validity of such information for small businesses. I also discuss whether the models capture all the relevant variables in the context of small business borrowing and finally, whether bankruptcy is a relevant outcome variable to predict.

The scoring of commercial applicants was initiated by the pathbreaking Altman et al. (1977) paper that built on work by Deakin (1976). Deakin had previously investigated the association between financial ratios and failure. Following on Deakin's analysis, Altman pioneered the business Z score that he derived by regressing 7 accounting ratios against the likelihood that the business subsequently went bankrupt. He used a matched sample design of 53 bankrupt and 58 non-bankrupt firms and found that bankruptcy classification was quite accurate for up to 5 years prior to failure. His scorecard exhibited a minimum successful classification of the bankrupt firms of 62.8 percent when the holdout validation technique was used. However, it must be remembered that Altman et al. employed a matched sample design and so each bankruptcy had a 47.8 percent chance of being correctly classified in the absence of a model, based on the frequency of bankrupt and non-bankrupt firms in his estimation sample.

Turning to the 7 ratios used in the first zeta model, some ratios were chosen because they had demonstrated a high correlation with bankruptcy in previous empirical studies. The 7 variables were *'return on assets'*, *'stability of earnings'*, *'logged debt service'*, *'cumulative profitability'*, *'liquidity'*, *'capitalisation'* and *'logged firm's assets'* (a size measure). *'Capitalisation'* stands for the ratio between total capital employed and assets[5]. Their rationale for including this variable was that in previous studies the denominator, which is the value of the firm as perceived by investors, conveys information about the firm's future earnings potential (Beaver, 1968; Altman, 1968).

'Liquidity' is denoted by the ratio between current assets and current liabilities. It represents the ability of a firm to meet its liabilities as they become due. Altman et al. demonstrate that *'liquidity'* is negatively related to bankruptcy. However, they do not employ any a priori

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[4] P.515. Altman et al. 1994

reason for including *'liquidity'* as an estimator of bankruptcy other than to comment, once the regressions have been run, that it is predictive and therefore is worthy of inclusion.

The *'log of total assets'* is included in order to control for firm size where larger firms are less likely to go bankrupt. No a priori reason is cited by the authors to justify its inclusion.

The *'return on assets'* ratio is denoted by net income divided by assets. It proxies the profitability of the firm and is predicted to be negatively related to bankruptcy. Altman et al. point to previous multivariate studies by themselves and by Beaver showing *'return on assets'* to be 'extremely helpful in assessing firm performance' (Altman, 1968; 1973; Beaver, 1967)[6].

You may notice that the assets variable is used as the denominator in two of the three financial ratios namely *'capitalisation'* and *'return on assets'*. It is a feature of bankruptcy studies using accounting ratios, that the same variable can be used as the input into several accounting ratios. This overlap between accounting ratios typical of bankruptcy studies had implications for collinearity.

The variable *'logged debt service'* i.e. pre-tax earnings divided by total interest payments, carries no justification for inclusion. Possibly the reader is expected to assume that a firm that is comparatively less well able to cover its debt obligations, receiving little income relative to its outgoings on loan repayments and denoted by a low ratio value, is more prone to bankruptcy than a firm with a high ratio value.

The inclusion of the *'stability of earnings'* variables is justified on the grounds that business risk is often expressed in terms of earnings fluctuations. However, this variable did not enter the final model.

Although the pioneering analysis on bankruptcy prediction by Altman et al. dates from the 1970's, its acceptance by contemporary writers is confirmed by more recent analyses using accounting ratios (Bahnson and Bartley, 1992; Gilbert et al., 1990; Platt and Platt, 1991a and 1991b; Platt et al., 1995, Schellenger and Cross, 1994; Taffler, 1999). Hence Weiss (1996), in a more recent study uses variables similar to the original accounting ratios employed by Altman et al. (1977). These are as follows; *'capitalisation'*, *'liquidity'*, *'log of total assets'* and *'return on assets'*.

Table 4.1 outlines some of the other variables used in corporate bankruptcy studies. I will now summarise these studies because no credit scoring analysis into small business default is complete without reference to the literature on bankruptcy studies. Any analysis

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[5] This is analogous to a debt to capital ratio in the case of a small firm start-up employing little or no initial capital of its own.

attempting to fill a literature gap by estimating a small business scorecard should acknowledge the contribution made by bankruptcy studies, owing to their pivotal role in the literature of commercial default.

In **Table 4.1**, the variable *'leverage'* comprising debt as a proportion of market capitalisation or total equity is represented in all studies. *'Liquidity'* is defined in various different ways but here is interpreted as readily available or easily liquidable (*'quick'*) assets divided by current liabilities (Zavgren, 1985). In other words, this ratio is intended to show how the firm can honour its short term commitments such as payment of debtors. The size of the firm is either measured in terms of assets or market capitalisation. This is not a ratio but rather a control variable. The return on assets or profitability measure is denoted by some income measure as a proportion of capital employed, investment or assets. *'Quick'* assets are similar in some ways to the liquidity measure but this time are defined as readily available assets such as cash divided by total assets. This variable is referred to by Zavgren (1985) as the *'cash position'* variable. Finally, more recent studies have emphasised the cash flow position of the firm and have included cash flow ratios (Bahnson and Bartley, 1992; Gilbert et al., 1990; Platt and Platt, 1991a and 1991b; Platt et al., 1995, Schellenger and Cross, 1994; Taffler, 1999).

The rationale for using the Z score was that accountants had been using accounting ratios prior to the introduction of automated scoring in order to establish how a business was performing. Rising levels of liabilities and costs of servicing borrowed capital (flow measures) were divided by company stock measures such as capitalisation in order to produce a picture of how the company was faring. Given that rising levels of debt to equity, the stockpiling of inventories and exacerbated cash flow problems were historically associated with bankruptcy, Altman et al. (1977), as we have seen, incorporated these traditional warning ratios into a regression model. They thereby found how each variable contributed towards an explanation of bankruptcy when controlling for the other variables.

More recent commercial scoring studies employing the basic principles pioneered by Altman (1977) are relatively common (Altman et al, 1994; Gilbert et al., 1990; Goss and Ramchandani, 1995; Mossman, 1998, Piesse and Wood, 1992). The question to ask is whether the scorecard techniques employed in these studies are applicable to the SME sector.

In order to evaluate the bankruptcy studies, I start with the idea of the matched sample design. This involves taking a sample of bankrupt and non-bankrupt businesses in order to

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[6] P.34 Altman et al., 1977

perform the estimations. The number of bankrupt and non-bankrupt firms is kept roughly similar. For example, Goss and Ramchandan (1995) used a paired sample of 20 solvent and insolvent firms, Lo (1985) derives a logit model using a set of 38 matched bankrupt/non-bankrupt firms and Goss and Ramchandani (1995) apply a matched sample of 20 bankrupt and non-bankrupt life insurers. This technique of matching the number of firms in each sample implies that the proportion of bankrupt firms in the estimation sample is vastly inflated. In reality, bankruptcy does not affect 50 percent of large corporations and therefore this first constraint of quota sampling firms means that the samples used in zeta-analyses bear little resemblance to the natural proportions of bankrupt and non-bankrupt firms in the population of businesses (Zmijewski, 1984). This has led bankruptcy studies to criticise the practice of matched sample designs (Piesse and Wood, 1992; Gilbert et al., 1990; Betts and Belhoul, 1987; Schellenger and Cross, 1994). The issue with matched sample designs is that researchers must apply the natural proportions of default in the population when applying the cut-off. They must modify the cut-off accordingly if the estimation sample contains a disproportionate number of bad companies (Thomas et al., 2002). However, Altman et al. (1994), when employing a large matched design containing 404 unsound and 404 healthy companies, do not mention how their choice of companies affects the cut-off. Because they do not mention the level of cut-off used, the reader is left considering whether the default equal probability level was applied. A further example of the problems raised when researchers fail to inform readers of why they choose a particular cut-off, occurs in Gilbert et al (1990). They compare the relative rates of *Type I* error (a business goes bankrupt while the model predicts it should not) with *Type II* errors (a business is predicted to be good while it is in fact a bankrupt). They estimate their first regression using a random sample of firms in addition to a sample of bankrupt firms. They additionally estimate a regression using a sample of financially distressed firms compared with a sample of bankrupt firms. They find that *Type I* error decreased when they used the random/bankrupt samples. However, *Type II* error decreased when they used their distressed/bankrupt sample. They used the same 50 percent cut-offs (expected probability levels for their classification matrices) in both cases, despite the fact that the natural proportions of failure in the population of borrowers was maintained at an artificial level of 50 percent.

Applying the reasoning outlined in Thomas et al. (2002), modified cut-offs should be used that would amend the cut-offs to reflect the real incidence of failure in the population.

These modified cut-offs are calculated in the following way.

Assign a company to the group of goods, *group 0*, if

$\beta^T x \leq \log C(1 \mid 0) / [C(0 \mid 1)] - \log [(n_0 \pi_1) / (n_1 \pi_0)]$

$= \log [C(1 \mid 0)\, n_1 \pi_0 / C(0 \mid 1)\, n_0 \pi_1]$ **4.1**

where

π_0 = population proportion in *group 0*

n_0 = number of cases in sample in *group 0*

$C(1 \mid 0)$ = cost of classifying a *group 0* member into *group 1* i.e. *Type II* error

The population proportions in the sample are;

$\pi_0 = n_0 / (n_1 + n_0)$

and

$\pi_1 = n_1 / (n_1 + n_0)$

then multiplying the proportion π_0 by n_1 gives

$n_1 \pi_0 = n_1 n_0 / (n_1 + n_0)$ **4.2**

and multiplying the proportion π_0 by n_0 gives

$n_0 \pi_1 = n_0\ n_1 / (n_1 + n_0)$ **4.3**

Cross-multiplying ***4.2*** by ***4.3*** we get $n_1\pi_0 / n_0\pi_1$. This gives 1.

Replacing $n_1 \pi_0 / n_0 \pi_1$ with 1 in ***4.1***, gives the following; we classify into *group 0* if

$\beta^T x \leq \log [C(1 \mid 0) / C(0 \mid 1)]$ **4.4**

Returning to the example cited from Gilbert et al. (1990), it is highly unlikely that the separate incidences of bankrupt and financially distressed firms in the population of commercial borrowers amount to 50 percent. Given that bankrupt firms are also financially distressed but that not all financially distressed firms are bankrupt, there should be a higher proportion of financially distressed firms in the population than bankrupt firms. If the researchers had considered the real proportions of the two types of failure in the population of borrowers and adjusted the cut-offs accordingly, comparability between the models would not be hampered by this limitation.

This lack of emphasis of why particular cut-offs are used in some of the bankruptcy studies, makes comparability among studies problematic. This is because classification rates are directly affected by the researcher's choice of cut-off.

A further problem raised by using a matched sample design is that distressed firms are included in the estimation sample because they are known a priori to be distressed. Anecdotal evidence from bankers suggests that the inclusion of already failed firms in estimation samples is incorrect[7]. Some evidence in the literature corroborates this anecdotal evidence. Dietrich and Kaplan (1982), quoting from Benishay (1973), indicated that bankruptcy studies using matched designs resemble more an '*autopsy of deceased firms rather than a prediction of business failures*'[8].They conclude that zeta-models would have more value if they did not preselect financially healthy and bankrupt firms. Rather zeta-models should include in their estimation samples dichotomies such as distressed and surviving firms or distressed and bankrupt firms. A problem with the estimated zeta models is that they preselect winners and losers, either category exhibiting very different financial ratios to begin with. Since distressed firms that survive and distressed firms that fail will have more similar financial ratios, it is more of a challenge and more valuable to a bank to be able to differentiate between these two outcomes. Hence, Altman et al. (1994) have revised Altman's earlier system, employed in Altman et al. (1977), of comparing bankrupt companies with non-bankrupt companies by estimating a scorecard based on a surviving or '*vulnerable*' / bad or '*unsound*' dichotomy. Hence, Altman seems to have taken on board criticisms that bankruptcy models represent more an '*autopsy of deceased companies*', in his more recent research.

To discriminate between firms at risk that survive and those that fail is precisely what the Altman et al. (1994) considered in their analysis, which up to then had not been adequately dealt with in the literature. According to Gilbert et al., in the analysis mentioned above dealing with financially distressed firms as well as bankrupt ones, they conclude that;

'A stronger case could be made for information value if such (credit scoring) models discriminate between 'at risk' firms that survive and 'at risk' firms that fail'[9].

The second problem with the zeta-analyses is the timeliness of the accounting data. Since they are based on historical accounting data rather than application or performance data, the timing of financial statements is essential (Altman and Saunders, 1998). If data accounting data is not current, a problem arises. If a researcher collects accounting data pertaining to businesses at risk that fail, some businesses at time t_{-3} (3 years before the event outcome) may provide up to date information while others may supply accounting information that predates their current status. Therefore, the financial ratios derived from delayed accounts will not reflect the state of the businesses in the time window t_{-3}. Non-current data

[7] For example, the bank from whom I obtained my data took care when constructing their in-house scorecards to ensure that they eliminated firms who had been known to have defaulted from the estimation sample. They took this precaution in order that the scorecard assessed the probability that a firm fails, given that it is a good firm to begin with.

[8] P. 31. Dietrich and Kaplan, 1982

confounds analyses that attempt to match financial ratios with a particular time window because it misrepresents the firm's financial situation at the time of estimation (time t_{-3} in this example).

A related issue is the availability and validity of accounting data. Only VAT registered businesses above the £50,000 turnover threshold (in the year 2001) are compelled to present full, comprehensive accounts. Gower (1992) indicates that small and medium sized companies can produce summarised profit and loss and balance sheet statements. Small and medium sized businesses do not have to produce accounting information complying with the Accounting Standards. However, Gower notes that the argument for this exemption is not a cogent one. He asserts that certain small and medium sized companies wanting 'small to be beautiful', are likely to produce audited statements[10]. Perhaps small businesses hoping to impress their banks are among the SMEs who want 'small to be beautiful'. However, this must remain a conjecture. The Accounting Standards exemption means that micro-businesses that the bank would like to score, are not required to have accounting statements that could be used to score their applications.

Apart from the restrictions on the availability of small business accounting information, the validity of accounting data is another issue that can impact on both large and small businesses alike. Accounting data can be manipulated to make the business look better than it is. Zavgren (1985) found that the explanatory variables with the most significant t-values in her model, were quick asset ratios e.g. acid test ratio because they are difficult to fake by entrepreneurs. She found that profitability figures are not significant, perhaps because they are easy to misrepresent. Therefore creative accounting practices can undermine the effectiveness of scorecards that are built on historical accounting information. It should be noted that some research has shown profitability to be a useful determinant of bankruptcy (El Hennawy and Morris, 1987; Altman, 1977).

Perhaps the most important consideration in this discussion of the limitations of Zeta models and the applicability of the Zeta model to small business scoring, is the explanatory variables used. Incorporated businesses have a very different ownership structure to small businesses with limited liability. Due to the higher dispersion of ownership in the larger incorporated businesses, there has thitherto been no need for including human capital variables such as principal partner's work experience in commercial scorecards. This is because when the management and ownership of the business are only tenuously related to

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[9] P.161. Gilbert et al., 1990

the principal partner, the expected explanatory power of human capital variables related to the business principal is reduced[11].

Asch (1995), who is a practitioner in the area of credit scoring, indicates that human capital variables are important in the scoring of small businesses. He describes the RMA/Fair Isaac initiative using pooled data to develop scorecards for small business loans of up to $35,000 and those greater than $35,000. He draws an important distinction between techniques for assessing larger corporations and smaller businesses. Small business lending is more comparable to consumer credit since qualitative information, such as the credit standing of the principal, is a requisite.

Leonard (1992), in his research into the scoring of 'small business' loans, did not employ accounting ratios as explanatory variables[12]. Instead he modelled whether a business was accepted or declined for a loan based on application details such as the name of the company, the amount of loan requested, the gearing (credit position) of the company and whether it was a new or existing company. A full listing of the variables used in the Leonard analysis is contained in **Table 4.2.**

The reason why I focus on Leonard's analysis is because it is the first published analysis of commercial businesses using explanatory variables that are stand-alone rather than accounting ratios. Additionally, some explanatory variables used describe the human capital of the owner. Therefore, Leonard's estimations are the first to demonstrate that variables, such as whether a company is an existing company or a start-up, when used in the scoring of consumers for credit, are significantly related to the outcome variable i.e. whether a business had his loan application accepted or not. Leonard calls attention to the failure of commercial scoring studies to emulate the methods used in non-commercial scoring.

'While the consumer credit industry has widely accepted and adopted the principles of credit scoring, the same cannot be said for their counterparts in commercial credit...we show that the same benefits that have been explored by consumer credit are available to those in the commercial area'[13].

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[10] P.470. Gower, 1992. 'Gower's Principles of Modern Company Law'. 5th Edition. London. Sweet and Maxwell

[11] Of course, it could be argued that the integrity of a high-profile CEO is immensely important in large companies where goodwill and fair play play a prominent role e.g. Richard Branson of Virgin Corp. However, my argument concerns more the financial composition of small businesses whose stocks are non-traded and therefore whose ownership resides in the hands of a few principal owners.

[12] What Leonard implies by 'small business' in fact large by UK standards. His sample contains loans to businesses with assets of less than $10 million and for loans of less than or equal to $1 million.

[13] P.89. Leonard, 1992. IMA Journal of Mathematical Applied in Business and Industry.

Leonard's study is not the first to undertake modelling the decision of a loan officer to lend or decline credit to an applicant. Overstreet and Kemp (1986) estimated the probability that loan officers in three US Credit Unions declined applications by potential borrowers. He indicates that the *'analysis of repayment performance'* must be left as an exercise for future research since his decision-making model does not consider actual repayment outcomes.

The importance of Leonard's study, is that it is the first to depart from the use of accounting ratios. Also, Leonard's analysis is the first, prior to Altman et al. (1994), to estimate a small business scorecard explicitly for small business loan applications. On the basis of Leonard's study, it is easy to visualise how similar, stand-alone, human capital variables could be adopted for use in commercial scoring studies. For example, stand-alone variables such as age, number of years at current address or residential status have been successfully used in consumer credit studies (Banasik et al., 1996; Crook et al., 1992c; Desai et al 1996; Desai et al., 1997). The unique feature of Leonard's analysis, therefore, is his usage of stand-alone as opposed to ratio type variables. For example, instead of dividing income surplus by the total net worth of the company to derive a ratio equivalent to the return on assets ratio described in **Table 4.2**, he leaves them as single variables.

Apart from Leonard's usage of straight variables rather than accounting ratios, there are several other differences, which distinguish his work into small business scoring from the bankruptcy studies outlined earlier. Leonard takes on board the possibility that small businesses below a threshold size are not obliged by law to have full profit and loss, nor cashflow statements. Some may submit their accounts in a summarised format (pro-forma) and others not submit any at all. He therefore includes a dummy variable '*ST*', indicating the format of the financial statements (pro-forma or fully recorded) with a field indicating that no statements were presented at all.

Leonard also considers the ownership structure of the small business in his choice of variables, a consideration that is lacking in the bankruptcy studies. His dummy variable, '*TF*,' denoting whether the firm is a private company or not and his variable, '*NO*', indicating the number of owners of the firm, are potentially useful. This is because these variables capture higher ownership dispersion (lower risk) and the legal liability structure of the company, with implications for the ease with which the bank can requisition collateral following company failure. Limited companies have their assets protected by law with implications for moral hazard because if an entrepreneur enjoys protection, he may less averse to risk-taking behaviour. This is analogous to theories of wealthy individuals being less averse to taking risks as described by Cressy (1999). Also, businesses with a wider ownership structure enjoy a wider skills base and decisions are taken on a consensual basis, thus pooling the experience and wisdom of several partners (Burns and Clements, 1992; Bopaiah, 1997; Cressy, 1996a). This assumes that all partners are active and not merely sleeping partners. Businesses with wider ownership structures are also more likely to continue existing should one partner fall sick, die or simply wish to terminate the business. Clements and Burns (1992) discussed how a bank is very concerned that a business owner's succession is guaranteed, since this assures some degree of continuity into the future.

Unfortunately, Leonard's outcome variable *'outcome of application'* is not one that models default but rather the decision to accept or reject a loan. Therefore, as an application scorecard, it has limited use unless the bank wishes to formalise its acceptance procedures and replicate how it has given loans in the past. I also have an additional concern with Leonard's research where he lists the variable *'OUT'*, the outcome of an application for finance, as an explanatory variable. However, if he is 'predicting' the outcome of an application, the inclusion of *'OUT'* as a predictive variable leads to endogeneity. Unfortunately, there is no clarification in his paper of the latter issue and I assume that this variable was included in error on the list of explanatory variables.

This issue of Leonard's outcome variable leads us to the general issue of outcome variables in the literature. I look next at the relevance of bankruptcy as an outcome variable which is the standard used by the Zeta type model. This has been criticised by researchers who have opted for an outcome variable that is closer to the risk grade system used by banks. Because this final issue is very relevant to my analysis of small business default in **Chapter 6**, it will be described separately in the next section.

4.4 The debate about a relevant outcome variable

When modelling commercial default in an applicant scorecard, should a credit scorer use bankruptcy or some other measure of default as the dependent variable? This is a very important question in commercial scoring because it hinges on the complex nature of businesses. Even small businesses can potentially have many accounts and several business principals. If one of an entrepreneur's accounts goes into arrears or one of the business principals exhibits default on one of his personal accounts, does this translate into default by the enterprise? Consumer scoring is not as affected by how default is defined since, in many cases, a particular money transmission account (MTA) such as a current or credit card account is targeted for scoring, rather than the sum of all the individual's accounts and those individuals with whom he/she has a financial relationship. Hence, some consumer scoring studies have focussed on the severity of the default rather than the definition of default itself (Crook et al., 1992b). One of the reasons for the lack of discussion in the consumer scoring literature on the nature of, rather than severity of default, is that arrears on an individual's MTAs are comparatively easy to model. It is only when the combined impact of default over numerous accounts has to be taken into account, that the analysis becomes more complex.

Due to the complexity of business default, Zeta-type analyses have used bankruptcy as an outcome variable. The alternative to using bankruptcy as an outcome variable is to use in-house bank data such as credit grades. There are advantages and limitations to both types of outcome variables that I will explain below.

Altman and Saunders (1998) support the usage of credit scoring models using objective outcome variables such as bankrupt/non-bankrupt or default/non-default. They are critical of methods attempting to replicate the loan grade or bond rating decision because they argue that these analyses depend on a subjective dependent variable.

'A criterion such as bankruptcy/non-bankruptcy is preferable because the classifications are less subjective than ratings. Bankruptcy is a fact! A bond rating or loan grade is a subjective opinion; leading rating agencies often do not agree with each other on a suprisingly large number of cases. And we know that bankers often disagree as to the 'appropriate' risk grade. Models that are designed to duplicate 'expert opinion' accept highly subjective decision criteria'[14].

However, Altman and Saunders do not take into account the subjective nature of bankruptcy. Indeed banks themselves may initiate bankruptcy proceedings against a business, as was modelled by Wruck (1990) and Lawrence and Arshadi (1995). Two identical firms could exhibit the same signs of financial distress. However, owing to highly subjective factors such as better personal rapport and trust between the loan officer and the entrepreneur, one firm may be forced into receivership and the other have its debts rescheduled. Although Altman and Saunders claim that *'bankruptcy is a fact'*, they fail to acknowledge that ultimately the state of bankruptcy can depend on highly subjective factors such as trust, rapport or belief in an entrepreneur's ability. Therefore, one must bear in mind that bankruptcy itself is not an entirely objective outcome variable either. Evidence by Scott and Smith (1986) even suggests that bankruptcy (Chapter 13 filing) may be a preferred option by a small business wishing to keep its creditors at bay. Mester (1997) suggests that this is indeed the case. It is possible to argue that the decision to instigate bankruptcy proceedings is not entirely motivated by objective factors but may ultimately depend on the ownership structure of the firm. This is because as Wruck (1990) suggests, firms whose

[14] P.8 Altman and Saunders (1998)

ownership rests in the hands of many stockholders present difficulty to receivers because the stock has to be divided among a myriad of creditors. In this case, it makes sense to keep the firm as a going concern and hence a bank is keener to reschedule the firm's debt and ensure that it reorganises its operations.

Therefore, I would argue that bankruptcy is as subjective or objective an outcome variable as the loan grade grade of a business, given that bankruptcy is inextricably linked to the decision processes of the firm's creditors.

Further evidence of the subjective nature of bankruptcy is seen in the inability of a bankruptcy scorecard to distinguish between insolvency and bankruptcy (Piesse and Wood, 1992). Bankruptcy and financial distress are flagged in the same way by a commercial scorecard but what differentiates the two outcomes, is the decision taken by the creditors. If the creditors can effectively reorganise a financially distressed company and exert some influence over the organisation process, bankruptcy is a less attractive option. Therefore bankruptcy is not necessarily influenced by the accounting ratios used in the Zeta-model, to the extent that insolvency is. What forces the bankruptcy outcome, is the decision that that the bank or main creditors take in order to mitigate the damage. Not only are different explanatory variables called for in order to explain the decisioning process for bankruptcy to occur, (e.g. the concentration of creditors), but the end result may be influenced more by subjective factors not captured in the Zeta model.

Scott and Smith (1986) provide indirect evidence that bankruptcy is not a useful outcome variable. Taking a sample of 1,653 US small business loans they find that following the introduction of The Bankruptcy Reform Act of 1978, the price of lending to small businesses was increased. This was because more borrower assets were now declared immune from forfeiture by a bank, causing the bank to raise the price of credit as the cover offered by businesses decreased. The borrower also could prevent the secured creditors (including the banks) from immediately seizing any other assets. Keasey and Watson (1994) on the other hand, have looked into the effect of insolvency law on SMEs in the UK.

The point being made is that bankruptcy is influenced by both legal factors as much as by subjective factors and therefore it is incorrect to claim that it entirely free of subjective bias.

Small businesses (sole proprietors) in the US can now receive a 3 year (possibly 5 year with the court's permission) stay on the seizure of their assets by creditors. A small business experiencing financial difficulties has an incentive to file for bankruptcy knowing that this provides ample breathing space for a reorganisation of the business activities. If bankruptcy is a choice variable, it is not merrely endogenous to the accounting variables but also influenced by the bank and entrepreneur's actions.

Despite the relative abundance of Zeta-type analyses using bankruptcy as the default variable, there are relatively few analyses modelling actions taken by the bank using default or in-house risk grades as outcome variables. The only known examples of such analyses are by Orgler (1970), Dietrich and Kaplan (1982) and Srinivasan and Kim (1987). Perhaps one of the reasons for this paucity in the number of studies using the credit grade as a response variable, is that they require information from the bank itself whereas analyses modelling bankruptcy and using financial ratios, can obtain data for their estimations directly from Compustat or some other commercial database.

One example of a study using a subjective response variable is by Dietrich and Kaplan (1982). They replicate the probit technique (McKelvey-Zavoina) used in the bond rating industry to derive five narrow intervals, which correspond to different probability cut-offs.

Their model uses a response variable, similar to that used by Orgler (1970), and aims to reproduce the lending officer's classification decisions. In so doing, the Dietrich and Kaplan analysis shares some similarities with other models aiming to replicate decisions made by lending officers (Leonard, 1992; Overstreet and Kemp, 1986).

The McKelvey-Zavoina procedure assumes that there is a variable, *P*, measuring the riskiness or probability of default of a loan. *P* is a continuous variable, measured on an interval scale. It represents a linear function of a set of independent predictors describing the financial condition of the company. An ordinal version of *P* is estimated, which is denoted by the researchers as Z. They determine Z by assuming the four intervals $(-\infty, 0)$, $(0, \mu_1)$, (μ_1, μ_2), (μ_2, ∞) where μ_1, μ_2 are constants estimated from the data.

The intervals correspond to the loan classification categories as follows;

$P_i=0,$	then Z_i = category *I*
$0< P_i \leq \mu_1,$	then Z_i = category *IA*
$\mu_1< P_i \leq \mu_2$	then Z_i = category *II*
$\mu_2 < P_i$	then Z_i = category *III*

Where;

I: current (acceptable banking risk)

IA: Especially mentioned (weakness in financial position)

II: Substandard (adverse trends)

III: Doubtful (repayment questionable)

IV: Loss (uncollectible)

Dietrich and Kaplan select their predictor variables based on interviews with 10 loan officers from the participating bank, the financial statement analysis literature and bond rating literature. The dataset consists of 140 loans from a commercial bank, which are matched to firms on the Compustat database. Of these 140 loans, 109 are classified as *I*, 16 as *IA*, 10 as *II* and 5 as *III*.

The linear model derived by Dietrich and Kaplan and used in the subsequent classifications is;

$Y = -.390 + 6.41\ D/E - 1.12FFC + 0.664SD$

Where Y is the predicted score for a loan, *D/E* represents the debt/equity ratio, *FFC* the Funds from operations ratio and *SD* the number of years of sales decline.

They perform out-of-sample validations of their two functions as summarised in **Table 4.1**. They classify the observations of 140 loans granted in 1976, whose performance was observed one year from the time of application in 1977, using their model estimated on 1975 data (referred to as **model 4**). Using **model 4**, they correctly predict 1 of the 5 *grade III* loans, indicating a hit rate of 20 percent. While this hit rate appears low, of the 4 misclassified *grade III* loans, 3 were predicted to be *grade II*. Hence, it could be argued that **model 4** correctly predicts 1 of the 5 *grade III* loans as *grade III* (*'uncollectable'*), while a remaining 3 bad loans are predicted to be *grade II* or *'doubtful'*.

They then take 187 Compustat loans from 1975 and classify these using the 1976 function (referred to as **model 3** and estimated on data from 1976) in order to predict their status one year from the time of granting the loans in 1976. **Model 3** accurately classifies 1 of the 2 *grade III* loans. Although this may seem poor, the *grade III* loan that it misclassified, was classified as a *grade II* loan. Therefore, it correctly classified the *grade III* loan as a bad loan, albeit designating its status as *'doubtful'* rather than *'uncollectible'*. This suggests that while classifying the bad loans correctly as bad, **model 3** did not classify *grade III* loans as bad enough, thereby underestimating the severity of the default.

In order to summarise the discussion on a relevant outcome variable, there is no optimal response variable that can be used in a commercial scorecard. This is because of the complexity of default which relates, not merely to default on one account, but rather to default over many accounts of interconnected borrowers. Because of the holistic approach to default measurement in commercial scoring, finding a valid outcome variable has not been easy.

Despite limitations in using either bankruptcy or credit grade response variables, due to the subjectivity in both, they are the only available outcome variables so far to be used in commercial scoring. I would argue that they are both equally valid. However an advantage of using credit grades to summarise the commercial borrower's position, is that certain grades denote insolvency. On balance, it is preferable to use insolvency rather than bankruptcy as a response variable given that the transition from insolvency to bankruptcy is a matter for the creditors to decide i.e. is a choice variable and hence there is a danger that using bankruptcy as an outcome variable leads to model misspecification.

4.5 Conclusion

Despite the predominance of firm failure or bankruptcy studies, these are not applicable to an analysis of small business scoring. This is because they omit possible important human capital variables such as ownership structure, the age of the entrepreneur or behavioural attributes such as past insolvency.

The issue of an appropriate outcome variable is one that is central to commercial scoring. Altman and Saunders (1998) are particularly critical of analyses that do not include bankruptcy as an outcome variable. However, Dietrich and Kaplan (1982) have successfully used credit grade as an outcome variable. Notwithstanding, the successful usage of credit grade in the past, Altman and Saunders (1998) have a point in condemning subjective measures of default. There is no commercial failure study, including bankruptcy studies, that is entirely free from subjectivity. This is because bankruptcy itself is subject to the same criticism of subjectivity. In the US, from where the majority of bankruptcy studies originate, a small business owner has even an incentive to initiate bankruptcy procedures because he enjoys legal protection over his collateralised business assets under US law. On the other hand, sometimes a bank has an incentive to withhold bankruptcy procedures (Wruck, 1990). Therefore, it is a fallacy to understand bankruptcy as an entirely objective outcome. It is equally simplistic to regard credit grade as an entirely subjective outcome variable. The credit grade of *'unrecoverable'* in the definition used by Dietrich and Kaplan, may be designated as such for entirely objective reasons e.g. because the level of firm assets are insufficient to cover the firm's liabilities. Invoking this type of objective criteria in assigning credit grades to borrowers, indicates that the credit grade system is not necessarily free from subjective bias. It is quite plausible that any loan officer would designate an insolvent firm as *grade III*, although the intermediary category of *grade II* or *'doubtful'* may be prone to more subjectivity, depending on the loan officer's confidence in the entrepreneur's ability to repay the loan.

Consumer scoring studies do not exhibit the same problems with outcome variables as commercial scoring studies. This is because if the product is for a credit card or store card, there is invariably more consensus on what is meant by default. For example Crook, Hamilton and Thomas (1992b) experiment with consecutive and single missed repayments.

However, in the case of commercial scoring, the outcome variable has to relate to the creditworthiness of the business principal (sole-trader), the entity as a whole or some amalgamation of the risk over the principal business partners (partnership).

Therefore, the definition of an outcome variable is complex and fraught with the problems described here. I would have to conclude on this basis that there is no ideal outcome variable for a business scorecard but that all definitions have some element of subjectivity. As long as these weaknesses are noted, commercial scoring becomes a more honest and open procedure.

Table 4.1 Financial ratios and variables used in business failure studies

A sign before an 'x' below, denotes the sign obtained on the coefficient, if reported. Sign (+) if variable positively related to bankruptcy.

	leverage	liquidity	size or assets	return on assets	quick assets	cash flow ratio	Out-of sample predictive accuracy (%)
Altman et al, 1994	x	x	x	x		Trade indebtedness	T_{-3} neural network 86.2%; linear discriminant analysis 86.4%
Bahnson and Bartley, 1992	x	x (-)	x		x	x	No classification tests on holdout sample cited
Betts and Belhoul, 1987	x	x	x		x		T_{-5} 37.5 %
Dietrich and Kaplan, 1982	x (+)	x		x		Income/debt repayments (-)	[1]Model 3; 50 (Estimator built on data from 1976) Model 4; 20 (Estimator built on data from 1975) for grade III (severe default)
Gilbert et al., 1990	x	x		x (-)	x	x (-)	62.5 % with equal probability cut-offs
Goss and Ramchandani, 1995							[2] Using Lachenbruch leave-out-one validation; 62.5 % for Logit model and 75% for neural network model
Lo, 1985	x (+)	x (-) cash/debt	x	x		x (-) income/assets	No classification tests
Piesse and Wood, 1992	x	x	x	x			Using model by Altman et al. (1977) T_{-5} 1 bad correct for every 52.5 bads incorrect Using model by Taffler (1984) 1 bad correct for every 32.5 bads incorrect

* Market return not as ratio of assets; ** Return on assets; *** Quick ratio (liquid assets/total assets)

[1]Dietrich and Kaplan estimate their **model 3** on data derived from the financial statements of companies in 1976. They estimate their **model 4** on data obtained from financial statements in 1975. They then validate their regressions out-of-sample where the 1976 estimator (**model 3**) classifies the observations taken in 1975 on which **model 4** was estimated. In turn, the 1975 estimation function (**model 4**) classifies the subsequent performance of the observations taken in 1976 and on which the 1976 function was estimated. This is another way of performing an out-of-sample test by classifying the outcomes of data relating to a separate time period. For a fuller description of this analysis See **section 4.33**

[2] Goss and Ramchandani focus their analysis on estimating bankruptcy of life insurers. Therefore the ratios they use are specific to the life assurance industry. Nevertheless, it is also considered as a bankruptcy study

[3] Taffler (1999) uses z score as explanatory variable to predict market returns along with other explanatory variables such as leverage. However, he does not report the derivation of his Z-score but rather uses it as an input into his subsequent estimations of market returns

[4] Weiss, in an exploration of cut-offs, concludes that only when the cost of Type I error is 25 times that of misclassifying a good firm will his scorecard, that is based on variables from the scorecard pioneered by Altman et al (1977), result in cost savings to the lender. Therefore, he proves that Altman et al. were correct in setting a cut-off value of 35 (assuming that loans are homogeneous in size) where they argued that 70 percent of a loan is typically lost through default whereas the benefit from lending to a borrower is 2 percent. This gives a cut-off of 35 i.e. 70/2

Table 4.1 (Ctd.) Financial ratios and variables used in business failure studies

Platt and Platt, 1990	x (+)				x	x (-)	91% but no cut-offs cited
Platt et al. 1994	x (+)	x	x (-)	x		x (-)	No out-of-sample results reported
Schellenger and Cross, 1994	x (-) net worth/assets	(-)		x	(+) current assets/total assets	x	56% with equal probability cut-offs
Srinivasan and Kim, 1987	x	x***	x	x**	x		Logit 79%. No cut-offs cited
Taffler, 1999	x		x	x*	x	x	[3] N/A
Weiss L.A., 1996	x (+)	x (-)	x (-)	x (-)			[4]Outperforms naïve model for cut-off greater than 25
Zavgren, 1985	x (+)	x (-)		x (-) (+)	x (-)		No breakdown given

* Market return not as ratio of assets; ** Return on assets; *** Quick ratio (liquid assets/total assets)

[1]Dietrich and Kaplan estimate their **model 3** on data derived from the financial statements of companies in 1976. They estimate their **model 4** on data obtained from financial statements in 1975. They then validate their regressions out-of-sample where the 1976 estimator (**model 3**) classifies the observations taken in 1975 on which **model 4** was estimated. In turn, the 1975 estimation function (**model 4**) classifies the subsequent performance of the observations taken in 1976 and on which the 1976 function was estimated. This is another way of performing an out-of-sample test by classifying the outcomes of data relating to a separate time period. For a fuller description of this analysis See **section 4.33**

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Table 4.2 Variables used by Leonard (1992)

Company name
Company number
Outcome of application (approved or declined)
Amount of the loan application
Total credit postion (gearing) of the company
New versus existing company
Branch of bank
Type of loan (operating/term/small business loan)
Financial statements (past records/pro-forms/none)
Sales
Gross profit
Operating profit
Bad debts
Depreciation
Income surplus (loss) transferred to equity
Total net worth
Net working capital
Private/other company
Number of owners of firm
Owners guaranteed security in the company

Chapter Five

Extraction of the data

5.1 Introduction

The purpose of this chapter is to demonstrate how the data was collated from various sources within the bank and how it was refined in order to ensure that there would be a one-to-one correspondence between each applicant's characteristics and his performance data.

The data used in this study was extracted from a UK bank, the extraction of which took place between January and July 2000. The cleaning of this data continued until December 2000.

I do not think that I have discovered the definitive way of collating small business data. However, it must be understood that I worked under time and information constraints while undertaking the extraction process at the head office of the UK bank supplying this data.

This data had never been used before in an application scorecard nor in any other analysis. As such it presented great scope for research. The corollary and downside to the uniqueness of the dataset, is that because a large part the data had never been extracted before, it also presented a myriad of extraction problems. In many cases the employees at the bank, who were extremely busy because they were experiencing major changes in their corporate structure, could offer few insights on how best to aggregate business borrowers over the 1,068 variables that I was initially faced with. I had to work out many relationships on my own. Because of these constraints, it is quite likely that some information has been extracted in a less than optimal way. In a minority of cases, I have had to gauge the function of some of the identifier variables and aggregate the data in accordance with my understanding of the underlying linking relationships. In view of the challenging nature of this part of my research, I will attempt to explain using examples where possible of how the data fits together.

It is worthwhile noting that while the data did not produce very powerful scorecards (**Chapter 6**), my findings in subsequent analyses into the financing of small firms, produced results similar to those produced by past research. If the outcome of my research is therefore anything to go by, the data performed satisfactorily and so any errors occurring at this stage did not impact too adversely on my subsequent analyses.

Because the material in this chapter is highly specific, I will consign the detail of the extraction process to **Appendix A5**. Such detail includes lists of the individual variables. The interested reader can therefore refer to **Appendix A5**, for a more comprehensive overview of the data extraction process and detailed discussion of variables that gave particular difficulty, including some of the loan contract variables such as collateral amount and the amount borrowed. This chapter contains a summary of the process.

The structure of this chapter is as follows. I first describe the relational database format of the database from which I extracted the data. I then list the stages in the extraction process.

In the section that follows, I describe how flat files were created from the variables in the relational database. The section following this deals with the sources of my application data. I then describe the extraction of the performance data that took the form of risk bands and credit grades. Finally, I present a summary of this chapter.

5.2 The relational database

Business data is characterised by high fragmentation because of its links to multiple associated accounts and the interconnections among individuals related to the business. Therefore, in order to save storage space, it is sensible to use a relational database format.

The dataset, at source, was not stored in a flat file but in a relational database format because of storage considerations. A relational database is where the data is hierarchical and each part of the dataset can be related to another part via one or several link variables. Some core portions of the data are common to most other portions. However, some portions of the data contain only a small number of observations. An example of such a data field is *'Number of bad events'*. Few businesses have experienced either the personal bankruptcy of their directors and even fewer, of the business entity as a whole. Both of these events would be described as bad events by the bank. However, despite the low frequency of bad events and the low cell population this entails, this variable is essential to the analysis. Chandler and Johnson (1992) and Wiginton (1980) both highlight how the inclusion of performance data i.e. credit bureau data, can enhance the discriminatory power of a scorecard. Bahnson and Bartley (1992) have shown how cash flow variables inferring the performance of the business can enhance a scorecard including financial data alone. Therefore, it is imperative that as many performance variables as possible are included in the eventual dataset even if they contain a low incidence of cases.

In my example above dealing with past insolvency, instead of the database reproducing the matrix for each and every variable, it only reproduces the bad events and these can be linked uniquely to a customer, a customer's account or a customer's loan application via an identifier variable. I will now explain what is meant by an identifier variable.

Identifier variables link all these relational datasets together. Four different identifier variables were used in the dataset from which I extracted my small business loan dataset. These were *'apcu_id'*, *'appl_id'*, *'appl_ver_no'* and *'customer_id'*.

As I understand the origin of the link variables from discussions with members of the small business systems team at the bank, they were derived by a team of database consultants. The link variable *'customer_id'* is the easiest to understand and this was the variable that I retained in the eventual flat files that I took from the bank. This variable simply assigns a unique customer number to each customer, irrespective of whether he is a business or personal customer. In other words, Joe Bloggs may have several roles. He may be a business owner or alternatively he may have taken out a mortgage and have a car loan. However, he can be referred to in each case by his '*customer_id*'.

The explanation gets more complex with the remaining identifier variables. '*Appl_id*' and '*appl_ver_no*' are always used together, where '*appl_id*' denotes the number assigned to each request for finance submitted by the individual and '*appl_ver_no*' refers to the version of the request. In other words, the request may be modified where the bank regards the initial request as excessive or is prepared to change the terms of the lending contract in response to revisions made by the borrower to collateral presented or guarantees made. These two link variables are always used in conjunction with one another. These were the link variables that I referred to when I was looking at portions of the relational database outlining the customer accounts.

However, it is impossible to link the customer '*customer_id*' to his end account '*appl_id*', without considering any other players who may be involved in the same account. For example, a partnership may have applied for a loan. I will illustrate this scenario using fictitious names and data.[1] The bank denotes two hypothetical entrepreneurs, the Smith brothers Albert and Ronnie, by two unique customer identification numbers 23 and 32 respectively. The bank always, for data collation purposes, denotes one of the partners as the principal partner and therefore his form of customer identification number is described as the lead customer identification number of 23. Therefore, the lead customer identification number of 23 denoting Albert, ensures that he is designated as the principal.

The customer identification number '*customer_id*' therefore carries a suffix '*lea*' so that it becomes '*customer_id_lea*', allowing me to identify it as the lead customer identification number.

Figure 5.1 shows the three main link variables. From left to right we move from application level '*appl_id*' to application-lead applicant level '*apcu_id*' and, finally, to the unique customer level '*customer_id*'. '*Apcu_id*' represents a transitional identification variable providing the vital link between the loan or overdraft facility applied for and the eventual customer. A staff member at the bank indicated to me that while '*appl_id*' and '*customer_id*' represent real entities, the former denoting a borrower's application and the latter an individual borrower, '*apcu_id*' does not stand for any physical entity. It is merely an additional identifier variable. '*Customer_id*' was an important linking variable because it

[1] In accordance with the Data Protection Act, I had no access to names of bank customers

linked all customers with their respective repayment information in the form of credit grades and risk bands.

Tables in the database were linked on either *'apcu_id'* or the dual links *'appl_id'* and *'appl_ver_no'*. All tables with application characteristics could only be united to their corresponding performance data at a later stage via the link variable *'customer_id'* once they had been related back to their respective transition tables. These transition tables were *TD5APCU APP*_CUST (known as *TD5APCU*) linking on the variable *'apcu_id'* and *TD5APPL_APPLICATN* (known as *TD5APPL*) linking on the variable *'appl_id'*.

Before I commenced my work with the bank, I mapped out in a diagram format how the different tables should fit together. The original maps I used are illustrated in **Figure 5.2** and **Figure 5.3**. In these maps, the link table is located in the centre of the map and the tables that are being included by means of the link variables, are located on the periphery of the map. In **Figure 5.2**, the link variable in question is *'app_cust_id'*, otherwise known as *'apcu_id'*. In **Figure 5.3**, the paired link variables are *'appl_id'* and *'appl_ver_no'*.

There is not always a unique one to one relationship between the variables which link the dataset together (link variables) and the characteristics of the borrower. When there is a 'one to many' relationship between a link variable such as *'apcu_id'* and variables within a table, multiple observations were seen for any given link variable. Hence, all the tables seen in **Figure 5.3** exhibited one-to-many relationships with the link variables, *'appl_id'* and *'appl_ver_no'*. In **section 5.4** dealing with the creation of a flat file, this difficulty of multiple entries for any given link variable is described and addressed.

Given that there were 1,068 variables in all, the strategy used was to extract all possible variables that were known to relate to business borrowers even if all variables were not used in any subsequent analysis. I had to ensure that I had covered as many variables as possible during that first extraction period. This was because the bank wanted to minimise any disturbance to their staff's time and therefore was not keen on redressing any problems that would arise once the data had been extracted and their obligation to me fulfilled. The bank encouraged me to 'flatten' tables, where there were multiple entries, by applying my own criteria such as averaging, maximising or minimising values.

The 1,068 variables in the dataset related to about 90 tables and 60 partition numbers[2]. The data in these tables came from several sources, as described in **section 5.5** below. Originally, the application forms to be completed by prospective business borrowers were examined and

[2] A partition number is not a variable but a field that demarcates tables from one another similar tables. In other words, a partition number is inserted between blocks of variables that come from the same section of an application form and that deal, for instance, with the collateral position of the firm. They do not play a role in my future analysis because they are meaningless in themselves.

the variables noted. Information about the business applicant would have been entered into the *Personal Financial Profile*, the *Business Lending Checklist* or the *Business Financial Profile* form. Since a business is made up of the personal finances of the individuals involved as well as the overall business, estimating the viability of a business is more complex then estimating the viability of an individual. This is why the sources of information are diverse. The aim of any data retrieval exercise is to aggregate data relating to the personal finances of the principals as well as the official data about the performance of the business. The following description of the dataset outlines the documentation used by the bank to capture the application characteristics of the borrower.

5.3 Stages in the extraction process

The extraction process involved moving the data from the IBM mainframe where it was stored, using a software application. The data needed to be examined for flaws that arose during the transferral process. Finally the data needed to be anonymised in the sense that identifier variables such as *'customer_id'* needed to be changed in order to preserve the anonymity of the bank customer.

The first and second steps, the extraction of the data and the preliminary reduction of the dataset so that it relates only to business customers, can be performed together using the *'proc sql'* procedure in SAS. This procedure permits data to be extracted from a mainframe environment on which matching and selection criteria have been performed. This process also permits the elimination of observations that add no value to the end analysis. For example, personal customers with no business connection would represent a subset of the personal customer observations that could be omitted at this stage. This would help to reduce the dataset to a manageable size.

The second step involves examining the explanatory (right hand side) variables that do not have a one to one relationship with the link variable. It is essential that there is a one to one relationship between all variables and the link variable in order that there is a unique link that corresponds to a customer or a customer's application to the bank. Multiple entries for the link variable would rule out completely the possibility of performing a regression analysis of the explanatory variables on the dependent variable. This process of invoking 'banking rules' to reformat tables with multiple entries is elaborated upon in **section 5.4**.

This second step was deemed the most time consuming because the one to one relationship had to make banking sense. In a highly categorical table with many variables apart from the link variable, an intuitive pattern between the link variable and other variables breaks down. A system for identifying the variables responsible was used and the bank needed to be consulted on ways to derive a flat file that invoked banking rules for the aggregation and averaging of amounts.

The third stage involved fitting each separate component table together by two separate sets of link variables. About half of the tables containing the explanatory variables were linked with one set of link variables and the other half independently linked via a separate link variable. The resultant flat file would contain most of the explanatory variables needed for the analysis.

In the stage that followed, the linked tables were united to an intermediary table that contained a link variable common to both tables as well as a new but pivotal variable *'customer_id'*. This linking process was carried out in order to take on board the variable *'customer_id'*. *'Customer_id'*, in turn, would be used to link the application data of customers and their related business connections with the performance data.

The necessary response variables for my small business scorecard (credit grades) were included in the next stage of the extraction process. Both credit grades and connected risk bands were related at this stage to their corresponding application data[3]. Several estimation samples were chosen for different six-month time windows. These customers were matched with their respective credit grade and risk band information. Since performance data is collected at a discrete point in time, it was decided to select the customer risk band and credit grade for a point in time six months after the date of the estimation window. The estimation window itself spanned a longer period[4]. For management information purposes, credit grades and risk bands were released to, and captured on the system on 15th of each month. An explanation of the banks credit grades and risk bands is provided in **section 5.6**.

The next step involved anonymising potentially sensitive variables such as *'customer_id'*. This was to prevent against the data being misused by anybody with access to it. It was decided to subtract a constant from these sensitive variables, thereby creating a new variable and easing data extraction as the resulting variable is shorter in length. These new variables could still be used to permit links among the various tables on condition that the changes applied to all the tables and not just a subset of the tables.

The final stage in the data extraction process was to convert all extracted flat files to a portable format to enable them be read by PC versions of SAS and SPSS. This was

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[3] Credit grades were subsequently used in the scorecard estimations because they posed fewer statistical problems than risk bands. The bank estimated risk-bands in a complex procedure using many of the same right hand side variables as used in the scorecard. Risk bands also used credit grades as a right hand side variable and therefore do not represent an independent response variable. Credit grades on the other hand described the actual physical state of the customer's account. Grade *F* or worse, involved the physical reallocation of the credit to the Bad Debt Collections department.

performed using a macro developed by the in-house bank scoring team. This macro permitted the migration of the SAS data from the SAS mainframe to a PC at the bank. The resulting format that was compatible with my PC version of SAS was stored on a CD.

5.4 The creation of a flat file

The data in its raw format is highly categorical. In order to create a flat file format, the individual categories of each variable must be aggregated. Alternatively, the row value becomes a column value by naming a new variable for the category. An example of this is where there are several partners in a small business. This would be seen in several rows for the variable *'apcu_id'* where each row corresponds to one of the partners (**Table 5.1**). It should be noted that **Table 5.1** contains hypothetical data based on variables contained in the table *TD5OWNR* and is only used to illustrate the relationships underpinning the data.

'Apcu_id' represents the link variable. This should only have one unique value. *'Apcu_id'* exhibits multiple values because there are several partners in some businesses. For example *'apcu_id'* of 24 is repeated twice where each of the partners born 16th May 1943 and 2nd July 1935 has a 50 percent shareholding respectively. The creation of a flat file involves compressing these multiple entries into one by taking one of several options.

The first option would be to note only the first row for each value of *'apcu_id'*. Although this would not be ideal, the advantage of taking this measure would be that since the percentage shareholding *'percent'* is sorted in descending order, taking the first partner would ensure that the partner with the largest stake is considered in the analysis.

The other option would be to consider all partners with shares of at least 50 percent. This would allow partners with equal stakes in the business to be represented by variables *'partner1'* and *'partner2'*. The drawback of this approach is that if the majority partner owned 30 percent of the business, he would not be included in this analysis.

The solution would be to construct a clause that allowed for the first partner to be represented and the second partner to be also represented, if the second partner had a stake hold of at least 50 percent. This would combine both approaches. The final point to note is that information that relates to each of the partners must now be appended to the new variables *'dob_p1'* and *'dob_p2'*, for the dates of birth of partners with major shareholdings. This increases the number of variables by a factor of two. The number of observations, on the other hand, is reduced from 7 to 4. The percent equity each partner holds in the firm is now represented by the two variables *'%_p1'* and *'%_p2'* respectively (**Table 5.2**). Like the example presented in **Table 5.1**, **Table 5.2** contains hypothetical data rather than real data in

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[4] A more comprehensive discussion of the length of time windows for the estimation sample and the

order to illustrate how I dealt with relationships in the data. The point of this exercise is to limit the rows for any one observation to one and hence create a flat file format.

The difficulty in this part of the data extraction, is that some of the categories are not as intuitive as the above example. The value of the linking variable is therefore repeated without an apparent reason for multiple entries. In these cases where there did not appear to be any basis for multiple entries, the bank was consulted because the bank analysts had a fuller understanding than the researcher, of which variable was accountable for any increase in the number of observations in the data. The difficulty of identifying variables that caused duplications in the link variables increased, where tables had large numbers of variables. The example cited above dealing with business partners would have been further complicated, if there had been additional variables with multiple entries. The process of identifying which variables are at fault for duplications in the link variables, is analogous to unravelling a ball of string; each knot has to be separately undone before further knots are located.

Table A 5.2 in **Appendix A5** gives a list of all the variables extracted, their source tables and new variables created by me in order to reduce the number of observations for an individual borrower so that there was a one-to-one correspondence between each borrower and his application data. In some instances, variables were summed across a borrower e.g. the variable *'discount'* in table *TD5SECI* or the variable *'retained'* in table *TD5BURK*. In other cases, the average value was taken of the different values of a variable e.g. *'prop_in1'* from the table *TD5FACR*. Finally, sometimes a minimum or maximum function was used in order to render the data in a flat file format e.g. the highest interest rate margin if there were two separate interest margins for the same type of loan[5].

The next section briefly describes the origin of the application data. The section dealing with the origin of the application data concludes my description of the explanatory variables used in my dataset. The section following it deals with the performance data that was linked to my application data in order to indicate the performance of applicants at a time subsequent to their time of application.

5.5 Sources of the application data

The application data was derived primarily from several application forms of which the most comprehensive and specific to business borrowers was the *Business Lending Checklist*.

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subsequent performance of applicants is contained in **Chapter 6**.

[5] For instance, sometimes banks offer stepped-interest rate loans. For instance, the bank may charge 5 percent on the first £5,000 but drop the interest margin to £4.5 percent on the next £10,000, and so on. **Appendix A5** outlines in more detail how the individual interest rates were separated out first before applying the averaging function.

Due to an oversight at the time of introducing an electronic database of business borrower details, the system could not assign the link variable *'customer_id'* to new customers until July 2000. Some loan sanctioners in the bank branches managed to manually assign *'customer_ids'* to new customers thus permitting the researcher to follow up the repayment performance of these first time clients.

The database is almost primarily comprised of existing borrowers for which repayment information is available.

Personal Financial Profile

The researcher first examined the *Personal Financial Profile* and identified 75 variables. Only 17 of these variables were captured in the bank's dataset. Of these 17 variables, some such as occupation description were unusable because they had not been coded as categorical variables. Postcode was not included because it would breach data protection requirements (**Appendix 5.1**).

Given that there are more business principals than businesses, it follows that for every business applicant appearing in the *Business Lending Checklist*, there is at least one *Personal Financial Profile* application form. There is also data from the *Personal Financial Profile* pertaining to individuals that are not business owners. Relating this to the data capture process, it was a primary concern to have matched the finances of individuals to the performance of their businesses at an early stage in the data extraction process in order to limit the size of the resulting dataset.

Business Financial Profile

This form which was denoted by a *'D'* in the researcher's notation, supplied information relating to 90 questions of which only 5 were identified as having being captured by the bank in their data base (See **Appendix 5.2**). This form outlines information about other credit relationships the borrower has and looks at the issue of assets, guarantees and business ownership structure.

Altogether there were 1,068 variables, of which approximately 240 were contained in the forms described above. Some of the remaining variables comprise a mixture of behavioural variables such as account excesses exhibited to date, the details of enclosures such as statements the customer may have included with his application and finally actions taken by the employee monitoring the account. Finally, there are variables such as *'Partition Number'* and *'appl_id'* which are designed to identify tables or link tables with others.

Business Lending Checklist

The letter 'B' denoted variables from this form in order to identify them in the final bank dataset (See **Appendix 5.3**).

This data related to applications from existing business customers for between £15,000 and £1,000,000. The bank expected 12,000 of these applications each year. Since this data has been automatically captured since October 1997, this implies that there were theoretically two years of business data available for analysis. The data from the *Business Lending Checklist* forms could be related to the personal and business performance of the borrower on other accounts with the bank. There were also links describing customer details such as sector and length of connection. All of these applications were manually underwritten. Some of the fields contained the comments of the relevant lending officer that could not easily be transformed into code.

The *Business Lending Checklist* noted the adverse events in the borrower's borrowing history or the history of related businesses, gave a summary of debtors, creditors, balance sheet financials and sales. It also assessed the maximum borrowing requirement and business risks as well as requesting additional information of the borrower. Borrowers for whom there is a *Business Lending Checklist* available, offer more scope for credit analysis as the information is rich and quantifiable in many instances. Many variables from the *Business Lending Checklist* were captured by the bank and contained in their data warehouse system. Of 249 variables identified, 163 featured in the database although some had to subsequently be eliminated because they could not be easily coded (**Appendix 5.3**).

Some of these variables were categorical and the researcher had to refer back to the question in the *Business Lending Checklist* to visualise how best to recode the categories into one variable. An example of the need for such cross-referencing is presented in **Table 5.3** below where Question 42 in the *Business Lending Checklist* has four categories. These categories correspond to field B251 in the nomenclature that I used. The categories elicit responses to the question;

'In the customer's opinion, can the business continue to operate in the absence of the principal(s)?'

The response categories to the above are as follows; *'close_family_memb'*, *'key_employee'*, *'other_principals'* and *'no_principals_othe'*. These responses can be taken to mean that the business can continue to run with the aid of a close family member, key employee, another principal or finally, that there is no principal partner to assume the managerial role in the absence of the principal[6]. The example in **Table 5.3** is provided to show how a perusal of the bank's application forms was a prerequisite to understanding what the variables meant. It was often the case that not even bank personnel could clarify what certain variables meant in their abbreviated format and it was only by examining the documentation and matching variables with questions that their meaning became apparent and groups of categorical variables emerged such as those above.

5.6 The location of repayment information in the form of risk bands and credit grades

The one and a half years of application data from January 1998 until June 1999 was divided into three periods of approximately six months duration. Application data was available for each of these three periods. The first period was from January 1998 until June 1998. The second extended from June 1998 until December 1998. The third period comprised January 1999 until June 1999[7].

Risk bands were extracted in the initial stage because I could not, on my own accord, undertake the extraction of credit grades at the bank. The latter required extraction by authorised banking personnel and it was suggested originally that credit grades would not be available to me. In the event, grades were available and consequently risk bands were not used in the analysis because, unlike credit grades, risk bands predicted measures of likely performance rather than observed performance outcomes.

Credit grades represent objective measures of business repayment performance. They represent the physical transferral of the customer within the bank based on his ability to meet repayments. If a customer enters a credit grade status equal to or worse than *E*, this implies a transferral of monitoring authority from the branch level to management at bank operations level. The business is placed on a watch-list. If his performance deteriorates even further, it is assigned an *F* credit grade and transferred to recoveries where attempts are made to recoup money owed to the bank. Accounts with a credit grade status of *E* or worse are deemed bad by the bank's own in-house scoring team. I inferred this meaning of credit grade status by the usage of *E* grades as the response variable in the derivation of the bank's in-house risk bands.

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[6] Where variables are used in subsequent analyses, I supply their meaning that was crosschecked with the bank. The purpose of this chapter is to describe the extraction process rather than describe the individual variables

Dependent variable: Taking a global view of customer risk in the data extraction

The reason why an appraisal of business customer risk is more complex than an appraisal of normal borrower risk is because of the banker's exposure to several business and personal connections relating to the business. The decision to move a non-performing account from branch office to management control is taken, whenever any one of the borrower's *Money Transmission Accounts* (MTA's) is flagged. Hence, the motivation for assigning an *E* grade is initiated when any MTA is flagged as being in serious arrears.

This factor of multiple business accounts has implications for the data extraction process and the shaping of the subsequent analysis. Unless all possible business accounts are included for the business customer, there is a danger of model misspecification arising.

It was not possible for the researcher to view the excesses on all three non-performing accounts for a case such as that illustrated in **Figure 5.4**.

In the illustration, the borrower exhibits arrears on his working capital facility (a bad outcome) but at the same time does not exhibit bad behaviour on his two remaining MTAs (overdraft and personal account). The one bad event outweighs the two good ones in such a way that his credit grade is bad overall. In other words, the sum of the parts amounts to something different than the whole picture. This is because of the global view the bank takes of the finances of a small business. Because his fortunes are inextricably linked with his personal finances, it only takes one seriously bad event to prompt overall insolvency.

In this case, a fall in credit grade is a proxy for how the borrower is performing overall since it comprises a view taken by the banker on the business borrower's overall risk. This was the approach adopted by Dietrich and Kaplan in their assessment of risk (1982) when they used the Kelvey Zaviona bond rating technique to represent the credit grade as the dependent variable.

The bank had urged a global view to be taken of the business customer using their definition of risk (credit grade) as a dependent variable. This global view was also reflected in the bank's own risk band approach which integrates the entrepreneur's performance over all his accounts.

5.7 Conclusion

The aim of this chapter was to give an overview of the data extraction process. It is essential for an understanding of how many of the variables were derived and the relationship between the outcome and explanatory variables.

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[7] The remaining one year period from July 1999 until June 2000 captured the repayment information.

I described how I extracted the small business data from the bank's mainframe. Much of the process involved rendering the relational database into flat files that could be used in subsequent regressions. This involved looking into each separate table of the relational database matrix and relating the individual tables back to two core tables *TD5APPL* and *TD5APCU* in order to include all the four necessary identifier variables. When this process had been completed, the performance data in the form of credit grades and risk bands were integrated into the main dataset.

This chapter mapped out the concepts that I applied in order to link the variables. It also explains the steps taken to summarise the values over an applicant, either by averaging or taking the maximum/minimum value, when there were multiple values for one individual business applicant. This inevitably led to some data loss, but was necessary in order to create a flat file. However, all information leakages have to be viewed in a pragmatic way. It is not possible to examine the finances and human capital characteristics of small businesses without being cognisant that a small business represents a myriad of accounts each carrying different interest rates and collateral types. There is, additionally, not always a one-to-one relationship between the business owner and the various explanatory variables because, for example, there may be several business owners. For this reason, the bank itself employs aggregation techniques in summarising the business borrower attributes. However, the bank was not in a position to allocate personnel to extracting this data on my behalf and so I had to perform my own aggregation techniques. This chapter gives me the opportunity to reveal how the various aggregations were performed and by doing so, new variables created.

See **Figure 6.3** in the next chapter for an overall plan of the time periods.

Table 5.1 **Example of categorical data with multiple entries**

OBS	APCU_ID	Percent	Date_of_birth
1	24	50	16MAY43
2	24	50	02JUL35
3	48	50	02JUN62
4	48	50	21SEP64
5	50	100	17JUL51
6	59	50	20JUL53
7	59	50	23MAR42

Table 5.2 **Example of categorical data with unique entries**

OBS	APCU_ID	DOB_P1	%_P1	DOB_P2	%_P2
1	24	16MAY43	50	02JUL35	50
2	48	02JUN62	50	21SEP64	50
3	50	17JUL51	100		
4	59	20JUL53	50	23MAR42	50

Table 5.3 **Categorical nature of data**

Host table	Variable name	Type	Length	Location on *Personal Financial Profile*
TD5BUST	CLOSE_FAMILY_MEMB	CHAR	1	B251
TD5BUST	KEY_EMPLOYEE	CHAR	1	B251
TD5BUST	OTHER_PRINCIPALS	CHAR	1	B251
TD5BUST	NO_PRINCIPALS_OTHE	CHAR	1	B251

Figure 5.1 The three link variables

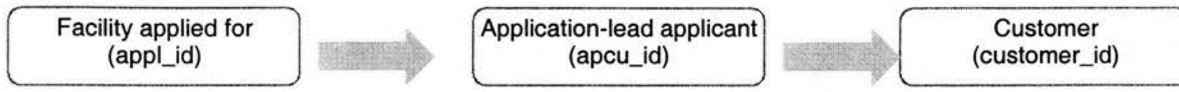

Figure 5.4 Fall in credit grade due to arrears on one money transmission account (MTA)

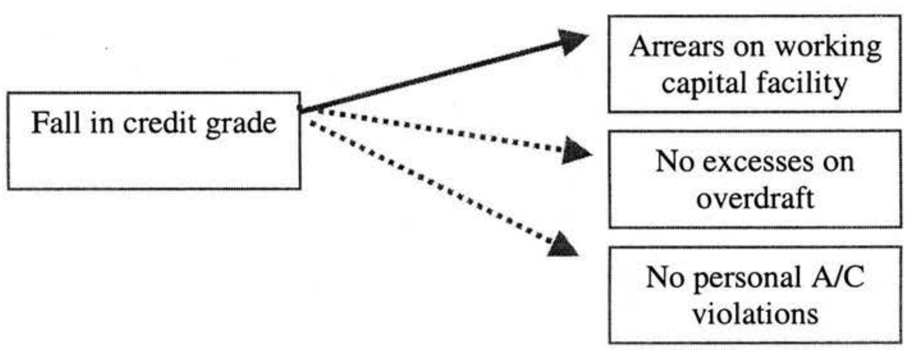

Figure 5.2 **Original scheme used at bank for linking the tables together using** TD5APCU

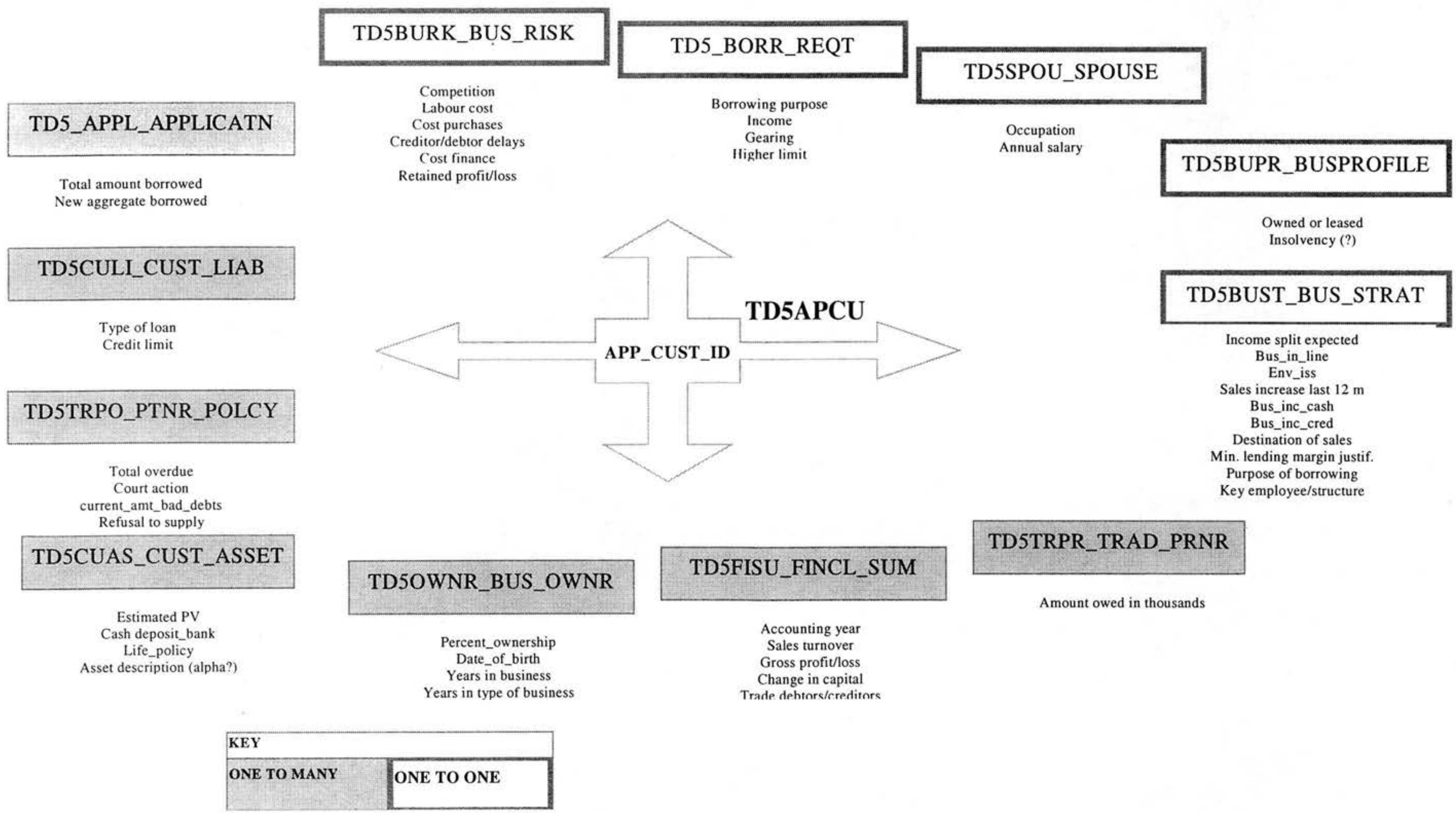

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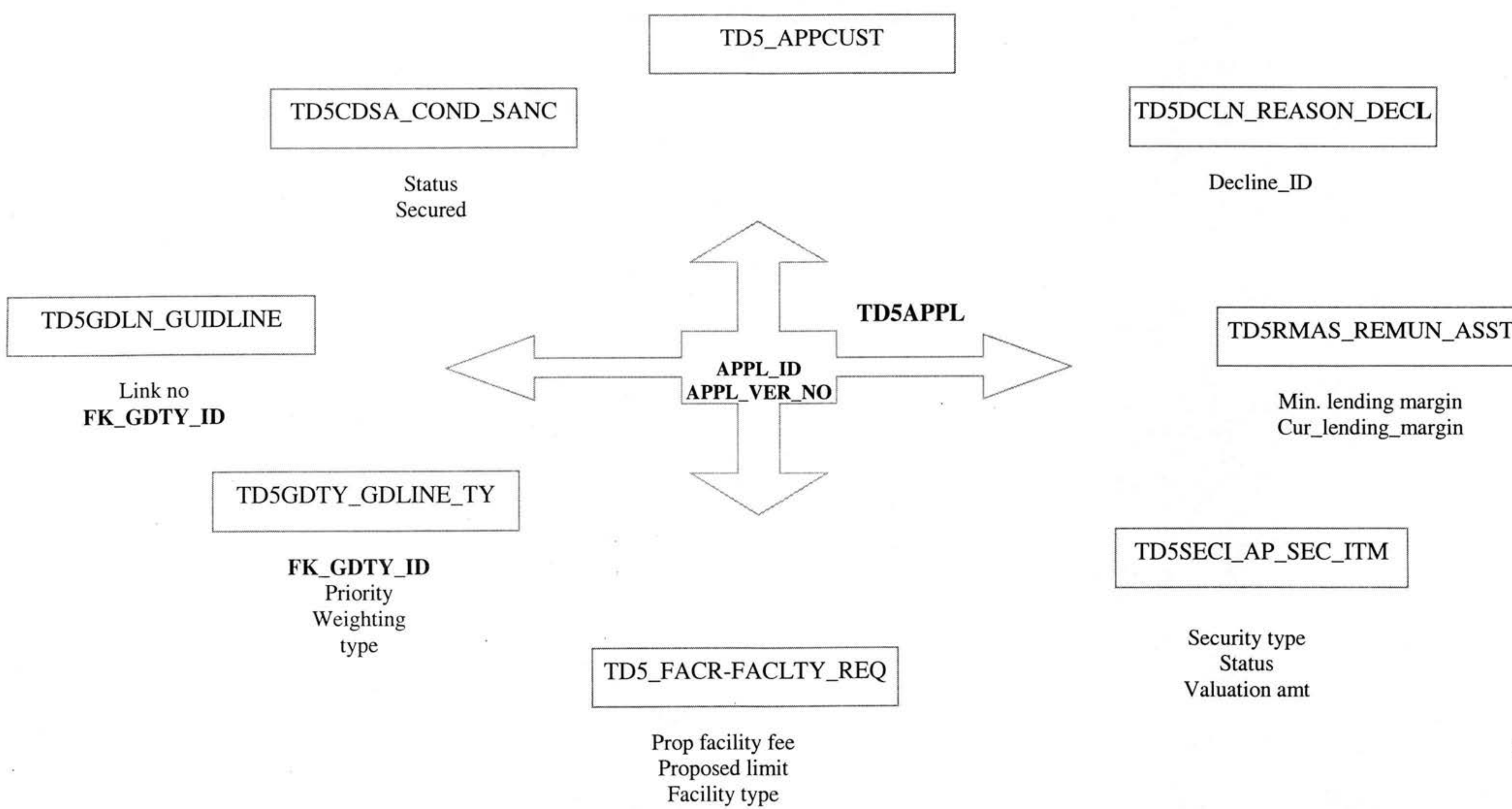
Figure 5.3 **Original scheme used at bank for linking the tables together using** TD5APPL



Chapter 6

Scorecard results

6.1 Introduction

The aim of this chapter is to present estimates of several business application scorecards based on different estimation samples of new small business applicants for both serious default and mild to serious default.

Application scorecards use the application characteristics from the application forms for a loan as explanatory variables. It is useful to derive these scorecards for several reasons.

Firstly, there is a paucity of small business scorecards in the literature. Where small business scorecards have been reported in the literature they have tended to focus on issues other than application scoring (Srinivasan and Kim, 1987). Alternatively, they are based on SMEs whose turnovers are comparable to the turnovers of large, established businesses as in Altman et al. (1994). In other words, the usage of the term SME to loosely denote small businesses can imply businesses with up to 500 employees and is therefore misleading (Bank of England, 2001). Commercial credit scoring as used by practitioners only considers loans of a magnitude associated with small or micro enterprises (Strahan and Weston, 1998; Asch, 1995). Therefore, studies such as that of Altman et al. (1994) do not adequately reflect the size of enterprises that are being commercially scored.

'..anecdotal evidence suggests that banks are beginning to lend to small business based on easily-obtained financial information. Moreover, Levonian (1997) finds that these credit scoring technologies have been applied mainly to very small business loans, those under $100,000, and have facilitated rapid expansion of these loans by very large banking companies...' [1]

The second main reason for this analysis is to discover whether the application data available to this bank, is sufficient to allow it make an informed decision on the applicant's creditworthiness.

Analyses of bank lending such as Cressy (1996a) have focused on the statistical significance of individual coefficients to show how the explanatory variables explain the response variable. However, the most robust test of how good a bank is at 'picking winners', to paraphrase Cressy (1996a), is to see how it would classify these applicants once a classifier has been estimated, using data from their loan/overdraft applications. In fact one of the most robust tests of the information regime a bank operates in, when lending to new business customers, is to test the classifier on an unseen or holdout sample of applicants. In so doing, I use a scorecard methodology.

In line with the credit scoring literature, I focus on the classification of business loan applicants. A main motivation for undertaking this analysis is in order to ascertain whether a loan sanctioner can perform better than chance when inputting the application details of a first-period business borrower into a scorecard. Therefore, the decision arrived at is non-judgmental (objective) and relies on observable information. Various financial economists have argued that is impossible to construct a small business scorecard because the main factors informing a lending decision are non-quantifiable and hence cannot be captured in a scorecard (Cressy and Toivanen, 1998; Doreen and Farhoomand, 1983; Syau et al., 2001). Such factors include trust, the ability of the entrepreneur to convince a sanctioner of his creditworthiness, his body language during the loan interview etc.

This chapter commences by giving some background information on business scorecards. It then gives a description of the data subsets used in the estimation of scorecards for the new business applicant borrowers. The data aggregation procedures and scorecard algorithm used such in the estimation of the scorecards, i.e. logistic regression, have already been described in **Chapter Five** and **Chapter Three** respectively.

The next section outlines how the weights of evidence method introduced in **Chapter Three** was implemented in order to organise the scorecard explanatory variables.

This is followed by a section delivering the within-sample results for the scorecards, followed by a section giving the out-of-sample results. Finally, the discriminatory power of my chosen scorecard that used a sample of 930 borrowers, *'Bigdata930'*, is compared with that of the other scorecards, where they were estimated from different subsets of the transfer/start-up borrower group at the bank. Reasons for the disparity in discriminatory power among the different scorecards for new business customers are outlined in this section. I then move on to discuss the most predictive variables in the *'Bigdata930F'* scorecard using a credit grade *F* as the response variable before summarising my findings in the concluding section.

I have described the methods of evaluating scorecards and emphasised the importance of ex ante or out-of-sample validation. I will also use classification matrices to evaluate the discriminatory power of my scorecard for one cut-off. In order to evaluate my scorecard over all the possible cut-offs, I will use the gini coefficient.

5.2 Some background on the scorecards

I have already described the more technical aspects of credit scoring in **Chapter 3** when I explained the use of logistic regression and weights of evidence.

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[1] Strahan and Weston (1998). P.824

In this section I provide details of the type of response variable used in the regressions that follow as well as describing the type of explanatory variables used. All the scorecards that I estimated use application data as predictor variables because an application scorecard, by definition, implies that the bank does not have access to any prior performance data.

My definition of default takes the form of credit grades. I use two definitions of default ranging from moderately bad to unrecoverable debt (stringent measure) and unrecoverable debt (less stringent). The stringent definition of bad implies a wide measure of bad that encompasses mild to serious delinquency i.e. *E* to *F* grades. An *F* grade is described as 'less stringent' because the customer's credit grade is allowed to deteriorate this far before it is designated as bad. Accordingly there should be fewer customers that are designated as bad under the less stringent measure, than customers categorised as bad under the stringent measure.

If an applicant exhibits credit grade *F* on his borrowing, responsibility for the loan is automatically transferred from the branch level to the bank's Bad Debt Collections Department at Head Office. A credit grade of *E* could be regarded as a stage most *F*'s would pass through in the transition from good to bad status. A credit grade of *E* is defined as the stage prior to the transfer of the debt to bad Debt Collections where the credit manager still has the authority to pursue the borrower for the overdue amount that is outstanding.

The *'ever F grade'* borrowers are furthermore a subset of the *'ever at least E grade'* borrowers because *F* is worse than *E* and is therefore included in the definition of *'ever at least E grade'* because it is the worst credit grade employed by the bank.

My methodology aims to develop several small business scorecards using ways of aggregating the applicant's accounts. Then the best performing two scorecards for each credit grade are further investigated.

I will use logistic regression rather than linear discriminant analysis because this is the industry standard (Thomas, 1998). It also avoids possible problems that could arise if the covariance matrices of the good and bad firms are not similar. In reality, previous analyses have shown that there is little difference between the two estimation procedures in terms of results[2]. (Leonard; 1992; Srinivasan and Kim, 1987; Hamer, 1983).

The organisation of the explanatory variables in my scorecard will follow the weights of evidence procedures used by Crook, Hamilton and Thomas (1991a) and described by Thomas (1998). This procedure provides an alternative to constructing categorical dummy

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[2] For a more comprehensive discussion on the comparison of logistic regression to linear discriminant analysis, See **Chapter 3**.

variables. The usage of dummy variables would raise the number of right hand side variables considerably, causing losses in the degrees of freedom of the scorecard estimation regression.

I have described the methods of evaluating scorecards and emphasised the importance of ex ante or out-of-sample validation. I will also use classification matrices to evaluate the discriminatory power of my scorecard for one cut-off. In order to evaluate my scorecard over all the possible cut-offs, I will use the Gini coefficient. I calculate the Gini measure for scorecard discrimination both within and out-of sample for these two best performing scorecards and the results obtained compared against the corresponding Ginis obtained for the other six scorecards.

6.3.1 Introduction to the new business customer scorecards

I have divided this section on the small business scorecards into two parts. The first part deals with the selection of the different samples that comprised the training and holdout samples for the scorecards. The second section deals with the different way I dealt with multiple business connection according to the scorecard in question.

6.3.1 Sample selection

What follows is a description of eight scorecards that I derived from the same data and an evaluation of the limitations and advantages of each. The names of these scorecards are as follows; *'Drastic618E'*, *'Drastic618F'*, *'Bigdata1572E'*, *'Bigdata1572F'*, *'Bigdata930E'*, *'Bigdata930F'*, *'SAScard930E'* and *'SAScard 930F'*.

Figure 6.1 illustrates how the initial sample of 1,572 start-up and transfer businesses was organised into the 3 main scorecards *'Bigdata1572'*, *'Bigdata930'* and *'Drastic618'*. A business start-up as the name suggests is an newly founded enterprise. This could either take the legal form of a sole trader or a partnership. All business start-ups were first time business borrowers. A transferred business is also a first-time borrower but of a different type. A business that has transferred its custom from another bank is described as a 'business transfer'[3].

[3] Although I do not have actual figures showing the relative breakdown between start-ups and business transfers, sources at the bank indicated that by far the majority of observations in the data relate to business start-ups (estimated at 1 in 10 by the bank). The transferred businesses were included in the application scorecard because the bank had no prior knowledge of their creditworthiness. However, these are likely to be larger and more established than the business start-ups. Despite the potential bias of including transferred businesses because of their larger size, we know from the theoretical literature

Starting from the 1,572 observations in the original dataset which was made up of small businesses with and without previous private borrowing and which was referred to as the '*Bigdata1572*' dataset, those with existing private borrowing were excluded to form the '*Bigdata930*' dataset. The latter dataset contains business loan applicants both with and without multiple business owners/principals. In other words, it is likely that this dataset contains a heterogeneous group of business owners some of whom have business partners and some of whom do not.

The '*Drastic618*' dataset contains a more homogeneous group of business principals than the dataset from which it was derived i.e. the '*Bigdata930*' dataset because only businesses with a one-to-one correspondence between business data and an individual account at the bank were considered. It is most likely that the '*Drastic618*' dataset represents businesses where the business principle is the sole provider of equity, collateral and uniquely responsible for the business project. With the '*Drastic618*' dataset there are no other family or business interest other than the proprietor's own interest.

The '*Drastic*' dataset contains observations that had no multiple connections i.e. there was a one-to-one correspondence between the business owner and his borrowing. The '*Drastic*' dataset therefore excludes entrepreneurs with several accounts or businesses that were run by more than one partner. The total number of observations was reduced from 2,768 (full, uncleaned dataset) to 618 when applicants with multiple connections or who had previous borrowing other than the new borrowing were removed. **Figure 6.2** how the SAS programme for structuring the dataset was set up. The performance information in the form of credit grades was fed in on the right hand side loop in the *PER9906* dataset while the application data was fed in the left hand side in the dataset *ONE1999*. You can see from **Figure 6.2** that the first step taken was to ensure that the borrowers has actually borrowed during the application time window. This was done by including borrowers who had an application number and hence whom I was certain had borrowed from the bank during this period. I next ensured that there were no multiple observations of the customer number '*d_fk_lea*' (a variable uniquely associated with each business principal or private customer as described in **Chapter 5**), by taking care that only the first observation of each customer number was included.

Then I had to carry out a number of exclusions in order to ensure that the entrepreneurs had time to exhibit default status. These exclusions are best explained by looking at the diagram

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that a bank is not likely to lend to a business that transfers from another bank due to adverse selection problems (See Chapter 2 regarding adverse selection and **Chapter 7** regarding *'informationally* that maps out the scorecard time windows (**Figure 6.3**). The application data and performance data were organised according to this timeline. This timeline allowed for a period of initial application followed by a period within which the applications could either default or otherwise[4]. The time windows are divided into the application period (white areas) and performance period (grey shaded periods). There are altogether three 6-monthly cohorts of borrowers applying during the application period.

Referring back to **Figure 6.2**, my first restriction was to exclude those 910 borrowers who had applied during the first period 1998 (first cohort) leaving 2,177 observations. The second exclusion refers to the 874 borrowers applying during the second period 1998 (second cohort) leaving 1,303 observations. I must also add that in addition to ensuring that borrowing was confined to the period within the 4-month time window (January to April 1999,) I adopted a further constraint used by the bank in their in-house scoring systems. In doing so, I excluded all observations relating to borrowers who were classified as uncreditworthy at the cut-off date of May 1999, when the performance data commenced. In other words, I filtered out any observations that has gone immediately bad in the four months before the performance window commenced. It might seem unusual that approximately 30 percent of borrowers (321/939) exhibited financial distress immediately after receiving their first loan but it must be remembered that as many as 20 percent of start-ups become financially insolvent in the first year of their trading (Barclay's Bank Information Service, 2000). Since financial distress is a precursor to bankruptcy, it is not implausible that this proportion is so high. Following the final exclusion, I was left with 618 observations relating to the 4-month period, January 1999 until April 1999.

The reason that I was so restrictive with my data and cut down the number of observations from 3,692 to 618 is as follows. Ideally, I would like to have included applicants from the first and second cohort because resulting sample would be larger and relationships between my response variable and the predictor variables easier to attribute to real rather than random effects. In other words, I would have had the benefit of working with a larger sample size with implications for sample variance. However, assume that I had included borrowers from the first and second cohort. An issue arises here of whether some businesses applying towards the beginning of the data time window e.g. a customer applying in July 1998 (from the first cohort) would have 22 months to turn bad before he had even entered the performance time window. Comparing this customer's likelihood of turning bad with the

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captured' borrowers).

likelihood of a customer applying in April 1999, just before the performance window, would bias the likelihood of a borrower exhibiting a bad grade towards earlier applicants.

The difficulty with the *'Drastic'* dataset is that I have forfeited many observations in the interests of a one-to-one relationship between the applicant and the loan. There is a trade-off between the integrity of the data and the size of the resulting sample.

6.3.2 Multiple business connections

In order to increase the number of observations in my estimation sample, I had to think of ways to reorganise the data upstream (at the stage of deriving the MERGED dataset in **Figure 6.2**) before the exclusions took place. This would allow me to include more observations from applicants in the third cohort. In so doing, I would increase my estimation sample as much as was possible without compromising the estimation sample by including borrowers who would have had a longer time to exhibit financial distress before the commencement of the performance window.

My solution to the problem of a small estimation sample was to review those borrowers who had been excluded at the MERGED dataset in **Figure 6.2** because they had multiple connections and therefore could not be identified uniquely by a customer number and ultimately a credit grade.

With this in mind, I derived the *'Bigdata'* dataset by aggregating all borrowing over a multiple business connection. I was able to aggregate the data in this way by taking the maximum values for the variables describing the interest rates, collateral rates and borrower age. This policy is in line with that employed by the bank. In the case of several business partners, they take the most mature partner.

The aggregation procedure used, provides an approximation of total borrowing over the connection and takes the maximum amounts in each instance. A weakness of this aggregation method is that the data diverges most from the reality of the borrowing situation when several almost equal yet different amounts are borrowed. An example of this would be where an entrepreneur had taken out a loan of £50,000 and an overdraft of £40,000. The aggregation approach means that the loan is the only amount considered because it is the maximum value. In reality, first time business applicants are only likely to take out one borrowing facility and so therefore this limitation does not arise in the majority of cases. The instances of multiple security valuations, loan amounts or other values that were almost

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[4] I used the same procedure used here to structure the application and performance data for the other scorecards.

equal in amount and magnitude were rare. It is fair to use this approximation in the knowledge that most of the dataset comprised borrowers who had a high core loan accompanied in some rare cases by a much smaller facility. The potential distortion caused by omitting any much tinier facility was therefore reduced.

When I compiled the *'SAScard'* dataset on the other hand, I identified variables such as borrowed amount and collateral amount where the distortions mentioned above could arise. The SAS Institute then wrote me a bespoke SAS programme that allowed me to aggregate potentially troublesome values in a meaningful way. Applying the example above with the £50,000 loan and £40,000 overdraft, the amount of the loan would be added to the amount of the overdraft.

Table 6.1 shows, by way of example, how the *'Bigdata930'* dataset differs from the *'SAScard'* dataset using the example of collateral as the variable being aggregated. *Business 1* and *Business 2* are identified by two separate identifier codes. These identifier codes most likely denote that there are other business interests apart from the main business principal who own collateral which was used in the business. For example, the business owner may have a piece of land with a collateral value of £6,300 while his wife/business partner has another piece of land worth £450 which is also taken as security on the loan. The technique used to aggregate the collateral and other such values where such multiple values exist for the *'Bigdata930'* dataset is to *take the largest value* in all cases. In the organisation of the *'SAScard930'* dataset, the values of variables such as collateral were summed if the values were different. However, only one of the values was taken if they were the same. Business 2 in **Table 6.1** is an example of the latter.

The reason for taking only one value for a variable such as collateral if it was repeated across the identifier variable, was that it was likely the collateral related to the same piece of land and by summing the values there was duplication.

Although this approach involves distortion if the multiple observations for collateral are very close in amount e.g. both parcels of land were £6,300 and £6,200 respectively with the exclusion of the £6,200 value, I argue that it is a useful approximation of reality. This is because in most cases, the values of collateral were very unequal, similar to the level of inequality seen in my example for Business 1.

There are two possible reasons why the values for collateral were so unequal. The first reason for collateral inequalities is that because collateral is difficult to monitor, the bank prefers to take an amount sufficient to or almost sufficient to cover the risk of the investment before taking a smaller amount if necessary to supplement the main core amount.

Such a policy would allow the bank to easily review the core amount and place emphasis on this while the ancillary amount were of secondary importance. The second reason for collateral inequalities is that all businesses in the *'Bigdata930'* and *'SAScard930'* datasets are first time borrowers with the bank. They do not have two facilities, one from an earlier period, being secured by a comparable amount of collateral. It is likely that the core collateral component is secured on the business premises or some other main piece of real estate. Small businesses are unlikely to have highly valued pieces of real estate to offer as collateral in the first place and so it follows that the large piece of collateral relates to their family home i.e. only piece of real estate.

'Bigdata930' is my own SAS programme written using its *'if first.value'* function and the sort facility. *'SAScard930'* is a bespoke code written for me by the SAS Institute[5].

However, whilst it makes sense to sum collateral amounts, it does not make sense to sum two different interest rates or percentages in general. So, in the case of percentages and interest rates, the average value was taken if the percentages were different and otherwise the maximum value was taken. In all, over 40 variables had their values averaged or summed in this way.

I can summarise my organisation of the different datasets as follows. The method I took in deriving the *'Bigdata930'* dataset involved taking the *'Bigdata 1572'* dataset and excluding borrowers who had previous borrowing. This was done to see how accurately I could predict default for those applicants with no previous borrowing connections and thus who were new applicants to the bank[6]. This reduced the number of observations from 1,572 to 930. I further reduced this number of observations by omitting any borrowers with multiple values for any variables such as borrowed amount and collateral amount to produce the *'Drastic'* dataset with 618 cases.

For all datasets, the categories of the 37 explanatory variables were coarse classified, finely classified and then weights of evidence assigned as described in **Chapter Two**. The next section explains how I applied the weights of evidence methodology explained in **Chapter Two** to my particular dataset.

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[5] It is important to underline here that I gave the specification for the *SAScard930* code to my contact at the company because SAS write technical solutions but the underlying solution which they translate into code, the aggregation technique in my case, remains with their client.

[6] At a later stage I looked at borrowers who already had borrowing connections because they are of interest when looking at business/bank relationships. (See **Chapters 7** and **8**)

6.4 Organisation of the explanatory variables

The weights of evidence methodology used in scorecards is described in **Chapter Two** dealing with the methodology and literature of credit scoring. This procedure was used by Crook, Hamilton and Thomas (1991a) and described by Thomas (1998). It provides an alternative to constructing categorical dummy variables that would raise the number of right hand side variables considerably causing losses in the degrees of freedom of the scorecard estimation regression.

The tables in **Appendix 6.1** show the calculation of weights of evidence for both my continuous variables and dummy variables in the '*Bigdata930E*' dataset. The values of the weights of evidence are calculated for variables grouped under 5 separate categories i.e. Assets and Collateral, Accounting Data, Entrepreneur Data, Distance and Miscellaneous Data and Exposure. The corresponding tables for the '*Bigdata930F*' are also included in **Appendix 6.2**

Table 6.2 shows an example of the grouping procedure used for the weights of evidence method where the variable being grouped is amount borrowed '*newsum*'. The corresponding groups are up to £4,000, greater than £4,000 but less than £40,000, greater than £40,000 but less than £100,000 and greater than £100,000. I will now explain the general rules I used to group my variables in this way.

When deciding upon where to locate the categories of the continuous variables several rules of thumb were applied as in Banasik et al. (2001). It should be noted there that there are guidelines that a researcher can apply when constructing weights of evidence. Despite taking care to ensure that the weight of evidence categories give good separation, there is evidence that scorecards using marginally different categories of the continuous variables can still achieve similar results. The predictions obtained are less sensitive to the usage of different categories than one would expect. This allows some but not much discretion over where to locate the categories. However, the main rule determining the location of the categories is to insert divisions such that there is greatest disparity in the bad rate among the different categories of the variable. As with most estimation techniques, a researcher wants to locate categories such that the difference between the groups is the highest whilst the difference among observations within a group is low (high within-group homogeneity).

The rules of thumb I used were as follows. I needed to compare the results obtained by the '*Bigdata930*F' with the '*Bigdata930*E' and so used the same categories for both. If possible, the values were multiples of 10, 100 or 1,000. I avoided using awkward values such 67.5

because a bank when using the scorecard will need to reuse it and therefore would be opposed to overfitting the scorecard.

Overfitting a scorecard, while possibly achieving excellent, predictive results within sample, may be less discriminating in future periods, with different data or on a holdout sample. Therefore, a person who estimates a scorecard is doing his client no service in overtuning the scorecard instrument. The rounding of awkward values is therefore permissible. I amalgamated categories where there were low frequencies of observations since the sampling error for such a category when calculating the percentages of goods and bads, would be higher.

A very large drawback of the data that was considered when constructing the weights of evidence categories, was the large number of missing values, which was over 50 percent for some variables. I had to balance the large number of missing values in the discrete 'missing value category' with the small number of values which remained to be assigned to separate non-missing categories. It is unwise to create a profusion of other non-missing categories when most of the observations are missing and the number of non-missing values in each category is quite low. This explains the reason for the small number of non-missing categories in many cases. Close examination of the percentages of goods and bads shows that there *are* differences among the non-missing categories even when the categories are relatively broad rather than too finely divided and dispersed. The use of broad categories increases the number of observations in each and so reduces the sampling error in each category.

An aid used when doubtful about where to locate the weight of evidence categories were the visual guides, examples of which are seen in **Figure 6.4** and **Figure 6.5**.

These diagrams show examples from *'Bigdata930E'* and *'Bigdata930E'* respectively. The variable in question is projected sales *'proj_sal'*. The first thick black curve in each of the figures shows the frequency of the bad rate across the categories when they have been coarsely classified into 35 groups with intervals of £20,000 worth of projected sales. The second thin black curve represents a 5-point moving average smoothing the first curve of the raw data. The formula for the 5-point moving average is;

$$\overline{x} = \tfrac{1}{5}(x_t + x_{t+1} + x_{t+2} + x_{t+3} + x_{t+4})\forall t$$

where x refers to the frequency of the bads in each coarsely classified category, t denotes the category and *x bar* refers to the 5-point moving average.

Finally, the third white graph shows the ranges of the final categories when they have been finely classified. The white 'weights of evidence' line does not track the 5-point moving average smoothed line for the highest ranges. Since most applicants' projected sales fall into the lower ranges, more 'weight of evidence categories' arise for sales under £11,000. After this, the relative frequency of observations is much lower for higher values (which is partially reflected in the variance of the bads frequency curve). Therefore in order to minimise sampling error, the observations for higher levels of projected sales are assigned to broader categories to retain similar numbers of observations in each group.

6.5 Within-sample regression results for grades *E* and *F*

The following two sections outline the predictive performance of the '*Bigdata930E*' and '*Bigdata930F*' business scorecards. This section deals with results for the *'Bigdata930'* dataset. The next section validates these results by testing them out of sample.

I will begin this section by comparing the distribution of good and bad borrowers over the predicted probabilities (cut-offs) in order to provide visual evidence of how discriminating the scorecards have performed. After looking at the visual evidence of how well the scorecards have performed, this section moves on to appraise scorecard performance using the standard procedures for appraising scorecards. The first of these procedures reports Gini coefficients (performance over all cut-offs) and the second of these procedures reports classification matrices (performance for a particular cut-off) for each scorecard. Finally, this section attempts to show how the bank could pursue a high growth strategy by maintaining a higher acceptance rate for small business applicants. This final illustration of how cut-offs are used in practice, aims to demonstrate how the bank could implement the '*Bigdata930E*' and '*Bigdata930F'* scorecards by operating different cut-offs depending on the scorecard used, growth strategy and cost structure of the bank.

Before moving on to measures of discrimination for my *'Bigdata930'* scorecards, it is useful to look first at the distribution of goods and bads over the range of predicted probabilities. The range of predicted probabilities show where the scorecards model the probability of an observation being bad ('*dummy*'=1) where dummy is my binary response variable for businesses which exhibit delinquency of '*ever at least E grade*' or '*ever F grade*' respectively. These are shown in **Figures 6.6 and 6.7**.

It can be seen in **Figure 6.6** where the response variable is '*ever at least grade E'*, that the distribution of bads is widely dispersed and less bunched towards the right than one would like. A discriminating scorecard should show 2 leptokurtic distributions, the distribution of bads located over the range of higher probability values (positively skewed) if the probability modelled is that of a observation being a bad. The corollary to this is that the distribution of goods should be located in the lower regions of the predicted probability levels (negatively skewed) and giving a right hand tail. With equal probability cut-offs i.e. a cut-off value of 0.5, observations with a predicted probability above 0.5 would be classified as bad and those cases with a probability of less than 0.5 would be classified as good.

One measure of discrimination, the classification matrix, shows the ratio between the two errors at a particular cut-off value. These errors represent the bads accepted and goods rejected or Type I error and Type II error respectively when the behaviour modelled is the likelihood of being a bad (See **Chapter 3**).

I choose 0.50 as the cut-off point for the classification matrix for two reasons. Firstly, I have little idea how the bank perceives the relative cost of lending to a firm that goes bankrupt compared to a firm that is creditworthy. If the bank is pursuing a growth strategy and the size of loans is small (e.g. under a pilot new business borrower loan scheme), it may tolerate relatively more *Type I* error that *Type II* error in order to capture a large portion of the market for first-period commercial borrowing. You will recall that the businesses in my '*Bigdata930'* estimation samples are all first time borrowers with the bank. If the bank were to extend relatively small loans to these first time borrowers with the intention of scoring these businesses by using their behavioural data that would be generated over subsequent periods, a policy of high cut-offs may be even desirable. The low per unit loss on these trial loans would be compensated for by the bank's success in having garnered a share of the commercial loan market, in the hope of profiting from it in subsequent lending periods. Given the high attrition rate of start-ups, it is likely that the bank will pursue such an incremental strategy, where lending small amounts on a trial basis is a precursor to lending at levels that reflect the small businesses' real demand for finance[7].

On the other hand, if the bank is sensitive to business failure, it will rate *Type I* error as more costly than *Type II* error and the cut-off will change accordingly. If the bank wishes to grow its commercial loan portfolio, a likely scenario if margins in the consumer sector are thin, it may be prepared to tolerate even higher cut-offs than 0.5 with the aim of retaining as much business as possible by accepting relatively more loan applicants.

In the absence of such information on how this bank evaluates the relative cost of *Type I* and *Type II* error, the default cut-off of 0.50 is the safest option. Furthermore, this is the level chosen in several empirical papers (bankruptcy studies) where researchers do not presume to know anything about the bank or insurer's cost-structure (Mossman et al. 1998, Wilson et al.1995, Goss and Ramchandani, 1995; Hamer, 1983). Using the default level of 0.50 is a conservative cut-off because existing studies suggest that the cost of lending to a bankrupt firm can be up to 30 times more expensive than withholding credit from a good firm. Therefore, any classification matrix at the 0.50 cut-off level understates the real number of bads that can be correctly classified if a lower cut-off were applied[8].

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[7] In a 1997 study, I discovered that Irish bankers were prepared to accept zero profits on a selection of their business start-up portfolio in the hope that they would recoup this investment in later periods

[8] See **Chapter 4** for discussion on cut-offs used in the literature

Figure 6.7 where the response variable is the less stringent measure '*ever F grade*', appears to discriminate better, in my opinion, than the '*ever at least E grade*' distribution[9]. This is because the distribution of bads is inclined slightly to the right of the peak for the goods, meaning that any cut-off in this region should eliminate comparatively more bads at the expense of comparatively fewer goods. However, it is unlikely that any banker would set a cut-off in this region (approximately 0.1) because he would be rating the relative costs of misclassifying a bad 'very highly'. This expression 'very highly' is a relative one. It depends on the cost structure of the bank although the cost of misclassifying a bad is normally expected to be more expensive than the cost of misclassifying a good and therefore equal probability cut-offs are unrealistic (Weiss, 1996; Altman, 1977; Hand, 1997)[10].

It is to be expected that the scorecard with the response variable '*ever at least grade E*' seems on the basis of the distribution of goods and bads, to underperform its '*ever grade F*' counterpart. This is analogous to the analysis by Hanley (2000), where I found the same pattern applies to scorecards estimated on consumer data, the second of which had a less stringent response variable '*at least 3-cycles delinquent*'. Generally, the more severe behaviour (less stringent measure of delinquency) being more pronounced, should be easier predict (relative to chance) in a scorecard and related to customer attributes than the milder behaviour (more stringent measure of delinquency). In the former case, '*ever grade F*', the type of default modelled by the response variable is more extreme. Judging by credit scoring analyses using extreme or less extreme definitions of default, the '*ever grade F*' scorecard should be more discriminating because it is more extreme (Gilbert et al., 1990).

We also compare the predictive performance of the two models using Gini coefficients.

Figure 6.8 shows the ROC curve for '*Bigdata930E*' with a Gini coefficient of 0.67.

'*Bigdata930E*', when validated within-sample, exceeds the minimum 0.50 threshold as is seen in the fact that the graph lies at all points above the 45^{O} angle line and $0.67 > 0.50$. However, the out-of-sample test of its predictive power in **section 6.6** provides a more accurate indication of how discriminating this scorecard is[11].

In order to obtain the 2-by-2 classification matrices for the '*Bigdata930F*' and the '*Bigdata930E*' scorecards, I first have to examine the output produced for the regressions

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[9] I make this observation based on visual evidence alone. A more definitive proof of the superiority of the '*Bigdata930F*' scorecard would be on the basis of its classification ability in a two-way matrix or its Gini coefficient.

[10] **Chapter 4** gives formula for the modified cut-off that was outlined in Thomas et al. (2002)

[11] All Ginis in this section were calculated using the 'full substitution' model i.e. the scorecard is trained and validated on the design sample. This is not to be confused with the 'full resubstitution' model Ginis calculated using the SAS Wilcoxon procedure outlined in the next section where training/holdout and Lachenbruch leave-out-one validation is used. The Ginis used here correspond to the ROC curves shown in **Figures 5.43** and **5.44**. The SAS procedure did not permit the creation of ROC curves for the 'full resubstitution' training sample Ginis and so these are not cited here for the sake of consistency

where the performance of the scorecards is described over the whole range of cut-offs. The output relating to the *'Bigdata930F'* scorecard is contained in **Table 6.3**. **Table 6.4** describes the output obtained for the *'Bigdata930E'* scorecard. Once I have investigated the raw output contained in these tables, I can derive the classification matrices at the 0.5 cut-off for the two *'Bigdata930'* scorecards. The simple, two-by-two matrices for the *'Bigdata930F'* scorecard is depicted in **Table 6.5**. The corresponding two-by-two matrix relating to the *'Bigdata930E'* scorecard is depicted in **Table 6.6**.

Table 6.5 shows that at a probability level of 0.5 for the *'Bigdata930F'* scorecard, of those observations which were correct, 5 were borrowers who turned out to be bad and the majority of the 790 good borrowers i.e. 785, were found to be good. These two values of 5 and 785 correspond to the cells a and d in the classification matrix outlined as described by Hand (1998)[12]. Of those borrowers incorrectly adjudged to be good or bads, 135 real bads were predicted to be goods whilst 5 real goods were incorrectly classified as bads. 135 and 5 correspond to cells c and b of the model classification matrix above. The corresponding sensitivities and specificities for the *'Bigdata930F'* scorecard can be calculated as follows below;

$Sensitivity = \; a/(a + c) = 5/(5 + 135) = 5/140 = 0.036 \Rightarrow sensitivity = 3.6$

$Specificity = d/(d + b) = 785/(785 + 5) = 785/790 = 0.9936 \Rightarrow specificity = 99.4$

Although only correctly detecting 5 of the applicants who exhibited an F grade during the 12 month period following the borrower's take-up of a loan when using a cut-off point of 0.5, this cut-off could be changed to reflect the in-house cost of classification errors at the bank. In this example, the bank would have achieved a reduction in ex post failure of 3.6 percent for the bad group at the cost of turning down 5 applicants who subsequently turned out to be good borrowers. If the bank had reduced the bad rate on ex post bad borrowers by declining a significant number of ex post good borrowers for finance, there might be more cause for concern. However, regarding the trade-off between goods and bads, the policy the bank adopts should be predicated on its cost structure. Imagine that the hypothetical cost of extending a loan to an ex post bad business is 10 times the opportunity cost of declining one ex post good borrower. In this case, the bank might be prepared to go as far as accepting the opportunity cost of turning down the applications of as many as 50 good borrowers. It would do this in order to have correctly ascertained the ex post risk status of the same 5 ex post bad borrowers.

For the *'Bigdata930F'* scorecard, the ROC curve is shown in **Figure 6.9** with a corresponding Gini coefficient of 0.70. This value for the Gini coefficient is placed well

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[12] See **Chapter 3**, **Table 3.2** for derivation of sensitivity and specificity

above the minimum value of 0.5. The curved graph lies above the diagonal representing the random model where the prior probabilities are arbitrarily assigned.

Turning to the '*Bigdata930E*' scorecard, the corresponding sensitivity and specificity at the 0.5 cut-off is calculated as;

Sensitivity = $a/(a + c) = 34/(34 + 244) = 34/278 = 0.122 \Rightarrow$ *sensitivity* = 12.2

Specificity = $d/(d + b) = 616/(616 + 36) = 616/652 = 0.9447 \Rightarrow$ *specificity* = 94.5

Although only detecting 34 of the applicants who turned '*ever at least E grade*' grade on their accounts, this model does so at a cost of turning down only 36 good applicants. In banking, where the costs are not likely to be equal and 0.5 cut-offs not used, more of the bads could be captured at a lower cut-off point, albeit at the cost of turning down more good customers. A printout of all the classification accuracies over the range of predicted probabilities shows the overall performance of the scorecard over all the cut-offs (See **Table 6.4**). The corresponding ROC curve for the '*Bigdata930E*' scorecard illustrates how well the scorecard performed over all the cut-offs. This has a Gini coefficient of 0.67, which likewise is better than the random model where the prior probabilities are arbitrarily assigned **(Figure 6.8)**.

Given that the relative importance of correctly turning down an ex post *Ever F* applicant compared to the importance of correctly declining an *Ever E* applicant, it is to be expected that the bank would operate different cut-offs for both scorecards. At a cut-off of 0.32 in the case of the '*Bigdata930F*' scorecard, for example, the bank correctly refuses loans to 16 bad borrowers at the expense of turning down 49 ex post good borrowers. The bank may choose to apply this cut-off point if the cost of correctly predicting the risk category of the bad borrowers is 49/16 or 3.06 times the cost of losing future business to an ex post good borrower. However, the trade-off is likely to be different for the '*Bigdata930E*' scorecard, because the meaning of bad does not necessarily imply terminal default and therefore the costs of being a bad are likely overall to be less than in the case of the '*Bigdata930F*' scorecard. In the case of the '*Bigdata930E*' scorecard, the bank may opt to retain a cut-off of 0.5 to reflect the relatively lower severity of incorrectly classifying ex post bads.

6.6 Out-of-sample regression results

Because scorecard estimates in the previous sample were not validated out-of-sample, the results obtained in the previous section need to be validated out-of-sample. It is easier to train and validate a model on the same set of data than on a holdout sample or other such set of 'unseen' observations. Hand (1998) describes the estimate of misclassification error (bads classified as goods and vice versa) by validating within sample as the *apparent* or *resubstitution* error rate. Overfitting of the model to the data can occur and this reusing of the estimation sample for validation can lead to underestimated error rates in samples that are small relative to the population. With larger data sets there is, however, less scope for overfitting. This implies that if my dataset is sufficiently large relative to the population, the results obtained in this section should be close to the results obtained in the previous section where the scorecard was tested within sample.

A fundamental question to ask is why should emphasis be placed on validating the two scorecards? Firstly, it should be remembered that I use credit grade as my response variable. Dietrich and Kaplan (1982) argue that out-of-sample (ex ante) validation is particularly important for commercial loans because of the subjectively derived response variable. In view of my subjectively defined response variable, it is all the more important to use a large enough estimation sample (close to the population size) and report results within sample or alternatively to test the model out-of-sample. Notwithstanding the small size of my sample compared with samples used in the consumer credit literature, it is large compared to the samples used in matched design bankruptcy studies, where samples of less than 100 are commonplace (See **Chapter 4**). Another factor underlining the need for rigorous model validation is the fact that I have 36 explanatory variables in my model that greatly increases the chances of model overfitting compared with Leonard's (1992) model that used only 19 variables.

The out-of-sample testing procedure is a little more complex than testing within sample. Two procedures were used to test *'Bigdata930E'* and *'Bigdata930F'* out-of-sample. The first procedure is the well known training/holdout technique. This entails taking a random sample (70 percent in this case) of observations and estimating the scorecard based on these training sample observations. The remaining 30 percent of the observations retained in a holdout sample are then used to validate the model.

The second procedure entails using the Lachenbruch (1965) method[13]. Hand (1998) argues that the advantage of this method is that the design set is almost as large as the entire data set. The estimate of the error rate is unbiased or any potential bias arises from the 'extra variation in the position of the decision surface due to using a design set of n-1 instead of n'[14]. In other words, the expected performance will be slightly worse when estimating on a training sample of n-1 observations than a training sample of n observations. Lachenbruch (1965) was the first to pioneer this method of reducing bias of the apparent error rate.

The Gini coefficients obtained on the 30 percent holdout samples are 0.55 and 0.60 for the *'Bigdata930E'* and *'Bigdata930F'* datasets respectively. The corresponding Ginis obtained on the 70 percent training samples are 0.71 and 0.73 although the latter is with full

[13] This entails using a SAS macro called *%CVpred* to estimate output which in turn can be used to produce unbiased Gini coefficients

[14] P123 Hand (1998)

substitution i.e. within-sample and so can be expected to be higher. Both out-of-sample Gini coefficients still exceed the 0.50 threshold. Therefore there is evidence that the probabilities are not assigned in an arbitrary way and that the models are better than random.

Using the Lachenbruch method, the Gini coefficients, *c*, are both 0.59 for the *'Bigdata930E'* and *'Bigdata930F'* models. This represents an improvement on the 30 percent holdout for the *'Bigdata930E'* models and a slight deterioration for the *'Bigdata930F'* model. Overall, the models outperform the random model when validated on a 30 percent holdout and using the Lachenbruch method.

It is interesting that the *'Bigdata930F'* model does not fit better than the *'Bigdata930E''* model on the basis that the *'Bigdata930F'* response variable is more extreme and hence should permit better separation of the goods from the bads. Contrary to what one would expect, both models are seen to be equally predictive when tested out-of-sample i.e. when resubstitution bias has been eliminated[15].

6.7 Comparison of the *'Bigdata930'* scorecards with other scorecards

The final issue is to compare the results from the *'Bigdata930'* datasets with those obtained when the application information was aggregated in different ways (**Table 6.7**).

The *'Drastic'* datasets which omit borrowers with other connections and focus on the simplest scenario of one borrower-one loan, perform nearly as well as the *'Bigdata930'* dataset which aggregated borrowers by maximising loan and collateral amounts. The *'Drastic'* models appear to be slightly overfitted because although they obtain higher Ginis over the 'full resubstitution' i.e. within-sample models than the *'Bigdata930'* models they perform slightly worse over the holdout samples and using the Lachenbruch leave-out-one validations.

The results in column (1) indicate the value of the Gini coefficient for the estimation sample. *'DrasticE'* shows a Gini of 0.75 on the 70 percent training sample. The Gini coefficient for the *'DrasticF'* model is 0.81[16]. The corresponding Ginis for the *'Bigdata930E'* and *'Bigdata930F'* models on the training samples are 0.71 and 0.73.

Looking at the Lachenbruch validations in column (3) , the *'DrasticE'* model exhibits a Gini of 0.58 compared with a Gini of .59 for the *'Bigdata930E'*. The latter is marginally better. For the models using the *F* grade as the response variable, both *'DrasticF'* and

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[15] A possible reason for the similarity in performance of the *'Bigdata930E'* and *'Bigdata930F'* models when tested out-of-sample is that with a smaller number of bads in the case of the latter (140 vs. 278) there may be greater sampling error

[16] Results on the training samples (Column (2)) can differ depending on the random sample taken but should approximate the results obtained using the Lachenbruch method

'Bigdata930F' have Ginis of 0.59 demonstrating that there is no difference in the samples used.

On balance the *'Bigdata'* scorecards perform as well using the Lachenbruch validation method, as the *'Drastic'* models. However, the *'SAScard'* models perform poorly out-of-sample, as evidenced by low Ginis of 0.44 and 0.43 in column (3) for the two models using the *Ever E* and *Ever F* specifications respectively **(Table 6.7)**. Furthermore, the *'Bigdata1572'* models perform better than the *'SAScard'* models but nevertheless are inferior when tested out-of-sample compared with the *'Drastic'* and *'Bigdata930'* models. This is demonstrated by Ginis of 0.57 and 0.55 for the *'Bigdata1572'* models when using the Lachenbruch.

This comparable performance of the '*Bigdata*' over the '*Drastic*' scorecards when using the Lachenbruch validation method, demonstrates that observations from borrowers with multiple borrowing connections should not be excluded from the estimation sample. These borrowers can be aggregated satisfactorily for two reasons. Firstly, being small businesses, these aggregations are legitimate since the borrowers *are their businesses* and so it does not cause a distortion by amalgamating their personal and business borrowing. Secondly, these businesses are small and are expected to have a short track record. Other business connections are expected to have negligible importance since we are not dealing with large corporations with the accompanying complexity of holding operations and affiliated groups.

Comparing the '*Bigdata930E*' and '*Bigdata930F*' scorecards with the corresponding two scorecards from the '*Bigdata1572*' dataset, which includes borrowers who have had previous aggregate borrowing, a different picture emerges. The *'Bigdata930'* scorecards perform better both within-sample and out-of-sample compared with the *'Bigdata1572'* models when looking at the magnitude of their Gini coefficients. The corresponding ROC curves comparing the '*Bigdata1572*' scorecards with their *'Bigdata930'* counterparts graphically illustrates the comparatively higher Gini obtained by the *'Bigdata930'* scorecard within-sample. The black line pertaining to the '*Bigdata930F*' scorecard lies above the white line relating to the '*Bigdata1572F*' scorecard over all the ranges of the cut-off score (**Figure 6.10**).

Figure 6.11 shows how the two *'Bigdata930'* scorecards perform within-sample when evaluated together over their range of cut-offs. Their performance is comparable, although the *'Bigdata930F'* scorecard performs marginally better as demonstrated by the higher position of the black line over the white one[17].

[17] Unfortunately, it was not possible to construct ROC curves for my Lachenbruch validation techniques because a different bespoke, estimation procedure was used in SAS to estimate this validation test and this did not generate the output needed for the derivation of an out-of-sample ROC curve. This is why the definitive test of scorecard discrimination is the Gini coefficient obtained for the Lachenbruch test because it is out-of-sample.

On the basis of the Gini coefficients for the Lachenbruch tests, the *'Bigdata930'* scorecard performs marginally better than the *'Bigdata1572'* scorecard. However, it only performs better than the *'Bigdata930'* scorecard when the response variable is *Ever grade F*. On a priori grounds, I decided against proceeding with the *'Bigdata1572'* scorecard despite its comparable discrimination and therefore it is not elaborated upon any further in this chapter. 642 of the 1,572 observations in the *'Bigdata1572'* estimation sample are likely to have a previous borrowing history. Hence the estimation data contains a confounding factor, in the case of the *'Bigdata1572'* data because this data also contains borrowers who have borrowed from the bank in a private as opposed to a business capacity before. In other words, some borrowers within this larger sample are likely to have developed entrepreneur-bank relationships prior to application for a business loan[18]. If this important explanatory variable is omitted because of data constraints, the model is misspecified because explanatory variables are excluded which could potentially be included. In a separate analysis using similar data it was found that such borrowers exhibit similar default rates than 'through-the-door' borrowers (Burke and Hanley, 2002).

It is incorrect to include such borrowers when estimating an application scorecard because they are not 'through-the-door' borrowers and so have to be excluded from the estimation sample. Although I would have liked to have estimated a performance scorecard for these borrowers, I was prevented from doing so by data constraints. My data does not capture the past performance of these borrowers over their mortgages, credit card repayments, education loans or personal overdrafts. Therefore, some potentially useful information is not available that would allow me to score the 642 observations from the *'Bigdata1572'* dataset who have pre-existing entrepreneur-bank relationships. Furthermore, my sources at the bank had asked me to estimate an application scorecard for first time borrowers because they had already successfully implemented several performance scorecards.

It can be seen in **Chapter 7** and **Chapter 8** that borrower reputation does play a vital role in determining the loan/overdraft interest rate for borrowers with some limited previous borrowing and the level of collateral submitted by the borrower respectively. Therefore, these 642 applicants within the *'Bigdata1572'* scorecard would more appropriately be scored using the previous repayment performance as an additional explanatory variable i.e. by constructing a performance as opposed to application scorecard.

The most important conclusion to be drawn from the comparison of the *'Bigdata930F'* and *'Bigdata1572F'* scorecards, is that bank personnel who estimate bespoke scorecards for first time applicants should eliminate any borrowers who have also got personal accounts with the banks. A failure to do so could undermine the discriminatory ability of the application

[18] **Chapter 7** gives a fuller description of entrepreneur-bank relationships and explores the issue of reputation.

scorecard. In other words, in order for an application scorecard to work, care should be taken that the estimation sample contains totally unknown businesses from the bank's point of view.

Perhaps a further implication of my results is the effect of data capture processes on scorecard results. Given the multi-faceted nature of small business account and application details, a person designing a data capture instrument should consider how the data is to be used. It would be useful if a system of rules could be devised a priori by a database designer that allowed easy aggregation of the data in a way that avoided duplication or omission. A user would then be sure of the integrity of the data and be able to apply filters in order to eliminate, for instance, borrowers who had borrowed before from the training samples.

6.8 Most predictive variables for *'Bigdata930F'*

This final section deals with the explanatory power of the individual coefficients for the *'Bigdata930F'* scorecard. I choose the *'Bigdata930F'* scorecard for this final analysis because the response variable *'ever F'* denotes the worst type of default possible and also to limit the scope of the analysis.

I will first outline the variables used in the scorecard before providing the rank order of the variables that were significant at the 10 percent level. Because I use the weights of evidence method of organising my explanatory variables, I rank the variables in terms of their explanatory power by referring to the significance level obtained on their t-statistic. For those variables that are significant, I present their weight of evidence chart in order to see the variation in the weight of evidence value across the ranges or categories of the variable. In so doing, we can visualise how highly non-linear the explanatory variables are. **Appendix 6.2**, referred to earlier, supplies the weight of evidence values for all variables used in the *'Bigdata930F'* scorecard.

The variables used in the *'Bigdata930F'* scorecard are listed in **Table 6.8**. We can see that there are 25 variables in all that were used in the final model when the backward elimination procedure excluded variables whose chi-squared statistic was less than 0.50. The excluded variables have not been entered into the regression there was likely to be collinearity between them and an existing variable. An example of a variable with a high level of collinearity is present gross profits *'Pgpgroup'* and present net profits *'Pnpgroup'*. Therefore, I only use present gross profits in my scorecard regression. The suffix *–group* means that the variable has been grouped according to the weights of evidence method.

Most variables are self-explanatory in **Table 6.8**. However, some may require some explanation. Account credit limit, *'aclgroup',* indicates the limit that an entrepreneur can draw down. In other words, his overdraft limit. *'Bpvgroup'* denotes the present value of the business asset. In the case of real estate purchases this would represent the mortgaged value of the asset. *'Cprgroup'* is a variable taken from the *Business Lending Checklist* indicating the breakdown between the proportion of sales by the entrepreneur that are in the form of cash compared with credit sales. It should convey the entrepreneur's working capital position. This is because entrepreneurs with high levels of cash sales are less liquidity constrained than entrepreneurs with high levels of sales conducted on credit. *'Psdgroup'* represents the drawings the entrepreneur has made from the business. On the other hand, *'rtngroup'* represents the amount of excess earnings he has been able to reinvest in the business.

Table 6.9 shows the most significant variables ranked by the significance level of their chi-square statistic. It can be seen that *'cprgroup'* the variable indicating the liquidity position of the business is first in the ranking.

I then looked at the bivariate correlations between all the variables in order to derive a reduced form model that only contained the most orthogonal (non-collinear) variables. **Appendix 6.3** shows the bivariate correlations on a variable by variable basis.

Eliminating the variables *'ryegroup'*, *'rtaggroup'*, *'pnpgroup'*, *'rplgroup'*, *'pgpgroup'* and *'psdgroup'* might seem extreme on first impressions but each exclusion has a reason. The first variable to be excluded was *'ryegroup'* because it was collinear with most others. In then concentrated on the concept of profits. The variable that consistently comes out higher in the chi-square rankings is recent gross profits *'rgpgroup'* and so this was retained. All other profit variables are by definition collinear with this and so are excluded.

There is an argument for retaining net profit variables. If I had a larger, cleaner dataset I would have given this more consideration but in my dataset the overlap with gross profit is too great and it is safer to exclude it.

I next turn to the concept of assets. The asset measure is encapsulated in the variable recent profit and loss balance statement *'rplgroup'* and *'rtagroup'* denoting recent total assets. Both variables are highly collinear with a bivariate correlation coefficient, which is significant at 1 percent. With 591 missing values *'rplgroup'* achieves an above average variable non-missing rate out of the list of accounting variables compared with 619 for *'rtagroup'*. *'Rplgroup'* is therefore chosen in preference to *'rtagroup'* as an asset measure.

My measure of how much firms are able to put aside from their operations in the form of savings is retained profit *'rtngroup'*. Although *'rtngroup'* is expectedly collinear with recent gross profit *'rgpgroup'* it is nonetheless included because it features highly on the ranking of significant variables for the *'Bigdata930F'* model and may be a proxy for how non-constrained small businesses are. All retained profit can be ploughed back into the business. Retained profit is therefore a more easily interpretable measure of the health of the business than even a net profit figure.

Finally, tidying up the list of variables to be included, I retain *'ldogroup'* the dummy for whether the business premises is owned or leased operating as an asset proxy. *'Psdgroup'* is excluded because it has a high number of missing values. It is not very significant in the equations so far and is perhaps difficult to estimate accurately by an entrepreneur.

Regarding the other variables for the model *'Bigdata930F'*, the same juggling exercise is performed between omitting variables on the basis of collinearity, their low significance ranking or a higher than average number of missing values. The easiest variable to omit is *'agrgroup'*, a measure of aggregate borrowing because this is collinear with *'nsmgroup'*, the alternative and more comprehensive definition of aggregate borrowing. Next to be addressed are *'olngroup'* and *'odvgroup* denoting other loan and other asset values respectively. These two variables do not feature highly in the significance rankings and there are a relatively high number of missing values. The next two choices regard tradeoffs between variables, which are collinear with one another. *'Bpvgroup'* is collinear with *'cprgroup'* and *'ldogroup'* is highly collinear with *'dyrgroup'*.

There is no a priori reason why *'bpvgroup'*, indicating the value of business owned assets, should be collinear with *'cprgroup'* indicating the proportion of the business funded by credit rather than equity i.e. gearing. Once again the decision rests on the number of missing values and the rankings achieved so far by the two variables. Since *'bpvgroup'* has 436 missing values vis a viz 428 for the variable *'cprgroup'*, the latter is preferred on the basis of having fewer missing values[19]. *'Cprgroup'* also features higher in the significance rankings and so is taken while *'bpvgroup* is eliminated.

The next tradeoff is between the variables *'ldogroup'* and *'dyrgroup'* that are collinear with one another. *'Ldogroup* indicates whether entrepreneurs have a lease or freehold on their

[19] In order to establish whether a value of an accounting variable was structurally or randomly missing, I benchmarked all the accounting variables on the recent net profit variable *'Rnpgroup'* which was one of the best populated accounting variables (perhaps because the bank issues instructions to personnel inputting the data or loan sanctioners to ensure that this field is filled). Therefore, if there were no recent profits reported and hence the *'Rnpgroup'* field was empty, other less reported were likely to be structurally missing because the firm had not filed statements. If the *'Rnpgroup'* was filled and the benchmarked accounting variable was reported missing, it was likely to be system missing because the firm had reported accounts statements. This issue of missing values only affected accounting information and therefore does not arise in the analyses in subsequent chapters because they rely on a more limited range on non-accounting information. However, since accounting information provides the basis of bankruptcy prediction models (See **Chapter 4**), it was deemed appropriate to use these variables notwithstanding the high level of missing values.

business premises and '*dyrgroup*' the number of years work experience the entrepreneur has. The variable '*dyrgroup'* has a very high number of missing values compared with '*Ldogroup*', 674 vis a viz 214 and so the former is chosen on the missing value criteria. Also, '*ldogroup*' does better on the significance rankings than '*dyrgroup*'.

Although the variables '*pjsgroup*' projected sales and '*bsmgroup*' the number of miles the business is from the bank are collinear, I decide to retain these for two reasons. Firstly, there is no a priori reason why projected sales should be linked to the number of miles a business is from its bank but most importantly, neither of these two variables have above average frequencies of missing values with 166 and 289 for '*bsmgroup*' and '*pjsgroup*' respectively. Finally, '*dprgroup*' is discarded because it has 511 missing values and might not be very robust.

The regressions for the *'Bigdata930F'* model are rerun for the noncollinear variables only and the rank order of the most significant variables is seen in **Table 6.10**. The standardised estimates are interpreted with reference to the weights of evidence diagrams for each variable. The most highly significant variables are as follows: *'cprgroup'*, *'rrpgroup'*, *'rtngroup'*, and *'ldogroup'*. The corresponding tables showing the weights of evidence charts for these significant variables are seen in **Figure 6.12** and **Figure 6.13**.

Once again *'cprgroup'* indicating the liquidity position of the enterprise is first in the rankings followed by the variable recent retained profit '*rrpgroup*'. In **Figure 6.12** we can see that entrepreneurs that have between 50 and 95 percent of their revenues in the form of cash and entrepreneurs that have none of their revenues in the form of cash (zero) are associated with lower default rates than any other entrepreneur group. Most worrying is the group who have over 95 percent of their sales receipts in the form of cash. This may represent difficulties faced by the catering or retail sectors.

Figure 6.13 illustrates the weight of evidence diagram for the variable *'rrpgroup'*. Those borrowers who report negative retained profits are associated with higher default rates as seen in the negative value for the weight of evidence. For borrowers with positive retained profits of less than and equal to £9,000, the proportion of bads is the lowest of all the categories as evidenced by the high plateau of the weight of evidence value at 0.8. Thereafter, higher levels of retained profits (greater than £9,000) are associated with higher default rates than those seen in the previous category.

The next significant variable is recent gross profit *'rgpgroup'* (**Figure 6.14**). This variable is not easy to interpret because it is highly non-linear. The weight of evidence for the first category, *'missing'* is 0.07 indicating a proportion bad of 14 percent. Businesses with no recent gross profit are more likely to exhibit higher proportional default rates of 18 percent, corresponding to a weight of evidence value of –0.226. The default rate then drops to approximately 13 percent on gross profits of less than or equal to £27,000 corresponding to a weight of evidence value of 0.13. The proportion bad rises for borrowers announcing gross profits of between £27,000 and £50,000 (weight of evidence value of –0.632) before finally falling to 13.19 percent for the final category where recent gross profit is greater than £50,000. Part of the reason for this variability could be induced by high levels of non-systematic variance within the subset of borrowers who reported recent gross profits. Only 330 borrowers reported gross profits out of the sample of 930 borrowers. However, there is an alternative explanation for this non-linearity. Firstly, I have to examine whether the non-linearity is induced by high non-systematic variance among the small subset of borrowers who reported gross profits from their financial statements.

I can address this issue by examining whether the same pattern is evidenced in the *'Bigdata930E'* scorecard. The weight of evidence values for *'rgpgroup'* for the *'Bigdata930E'* scorecard point to the same phenomenon. The highest proportion of bads from any of the groups is seen in the intermediary group where borrowers report gross profit levels of between £27,000 and £50,000 (**Appendix 6.1**). The proportion of bads in this category is 42.7 percent. Perhaps the reason for the high attrition rate for borrowers in this category is that these borrowers are likely to be experience a stage in their development when they need to expand or fail. Once firms achieve a critical size in terms of their gross profits, their failure rates diminish. Alternatively, there may be the case that firms in the £27,000 and £50,000 category start to over invest compared to other firms and hence starve their firms of the liquidity needed to repay their loans.

The next variable I examine is the variable *'rtngroup'* (**Figure 6.15**). This variable is similar to the variable *'rrpgroup'* but there is an important difference. While *'rrpgroup'* refers to the retained profits reported in the financial statements of the firm, *'rtngroup'* is a variable that is filled in by all applicants irrespective of whether they supply financial statements or not. This variable *'rtngroup'* is likely to be more reliable than *'rrpgroup'* because all respondents have replied to this question and hence there is no dichotomy between respondents who replied and respondents who did not reply. In the case of the variable *'rrpgroup'*, I had to interpret the influence of retained profit on default rates only for those respondents who had been asked to supply (or were in a position to supply) financial statements. There is more of a likelihood that an influence is systematic (a real trend) rather than non-systematic with higher numbers in the individual categories because the variation within each category relative to the variation between categories is reduced with higher cell frequencies.

I find that the category where the highest levels of retained profits are reported (greater than £40,000) is the one associated with the highest default level. This default level of 20 percent corresponds to a weight of evidence value of –0.344 (**Figure 6.15**). In order to ensure that this bad rate is not an artefact of the data, I cross-check this result against the result obtained for the *'Bigdata930E'* scorecard in **Appendix 6.1** and find that this category also reports the highest default rate in the other scorecard. It appears therefore, that borrowers reporting the highest levels of retained profits are more susceptible to failure. This seems counter-intuitive because we would understand retained profit to be a good sign of a firm's prosperity and ability to be self-financing.

Referring back to **Figure 6.13** that looked at retained profits but confining our analysis to businesses reporting their profits from financial statements, the same phenomenon is observed. You will recall that the weight of evidence value attains its maximum level for positive values of retained profit of £9,000 but that it decreases for values above this. This range of categories for retained profits is terminated at this fourth category because the number of observations in the final cell, if split any further, would yield very low cell frequencies (at least less than 30 observations). However, the same pattern is witnessed with respect to the variable *'rrpgroup'* as with the variable *'rtngroup'* where higher levels of retained profits are associated with higher default levels.

We can conclude from the possible positive association between retained profits and default that firms with higher levels of reinvestment, where they reinvest surplus profits into the business, are associated with higher levels of default than businesses with lower levels of reinvestment. This positive association between reinvestment level and default must be separated from the influence of surplus profit (before reallocation as investment in the firm or absorption by the business owner) which is negatively related to default, which you will recall from **Figure 6.14**. If we interpret the associations between reinvestment and default and profits and default, a consistent picture emerges of what is happening in the firm. Those business owners who do not see the need to grow and hence reinvest the surplus business profits back into their businesses, are likely not to be cash constrained as a result. Therefore, they have sufficient liquidity available to repay balances owing to the bank when they fall due. On the other hand, high levels of reinvestment may be coupled with high levels of growth in capital assets. However the payoff time for making this investment may be at a future stage. Meanwhile the firm is placed in a precarious position because it may not have much liquidity and hence default on its loan repayments. Hence if the retention of profits signals liquidity constraints, it is likely that high levels of profit retention is associated with above average business default.

The final significant variable, *'ldogroup'*, denoting asset availability is a variable that is used by the bank on its own in-house application scorecard (**Figure 6.16**). Contrary to the bank's recommendation that business owners who lease their business premises should be scored less highly than business owners who own their business premises, I find that <u>freeholders exhibit higher default rates than leaseholders</u>. In fact nearly 12 percent of leaseholders subsequently default on their repayments compared to 14 percent of freeholders. The weight of evidence value for leaseholders and freeholders is 0.264 and –0.116 respectively. However, the highest default proportion is reported for the missing category where nearly 17 percent subsequently default on their repayments. This corresponds to a weight of evidence value of –0.116.

This result is contrary to what we would expect given that freeholders theoretically have an additional asset with which to secure additional funding. However, the result is most likely to be driven by the fact that supposed freeholders do not have two assets to offer the bank as collateral. Many of the observations in this category are likely to relate to entrepreneurs who operate from their own homes. For example services such as plumbing, electricians, beauticians or hairdressers do not need a separate business premises but can operate quite successfully from their own homes[20].

The overall result of my analysis of the significant explanatory variables points to liquidity as being the foremost variable influencing business default rates. This conclusion is borne out in the negative correlation between gross profit and default. Furthermore, there is tentative evidence that the levels of retained profits, if indicative of business growth, reinvestment or liquidity, are positively correlated with default. This result corroborates the study by Weiss (1996) that indicates that the liquidity variable is one of the consistently important variables in influencing business failure.

6.9 Conclusion

In this chapter I have shown that it is possible for a loan sanctioner to use the information obtained on the application forms of a small business borrower in order to predict the risk of default during the period following application. My results show that the discrimination of these scorecards is better than chance, although not much better.

Of the eight small business scorecards that I estimated, six scorecards performed better than chance when validated using the Lachenbruch out-of-sample test. These were both *'Drastic'*, *'Bigdata930'* and *'Bigdata1572'* scorecards. I varied the response variable in each case to create *Ever E* and *Ever F* scorecards for each of the three samples.

My analysis is the first to prove that it is possible to estimate the risk of default better than chance using small business application data. The only other existing small business scorecards do not give a comprehensive account of how the scorecard is estimated by failing to describe either the aggregation procedures used, the classification accuracy obtained by the scorecards or the interpretation of the variables.

[20] This argument that supposed freeholders are in fact entrepreneurs operating from their own homes is reasonable given that the question in the bank application forms asks whether the business owner owns the business premises but does not clarify whether the business premises comprise the owner's home.

Hence Leonard (1992) estimates the decision to reject or accept a business loan but does not predict business failure once the loan has been accepted. Altman et al. (1994) do not disclose how the variables used in their estimation should be interpreted because on their own admission the usage of the neural network algorithm rules out an explanation of how the individual explanatory variables operate. Asch (1995) do not enumerate the variables used in the Fair Isaac small business scorecard and therefore there is also no interpretation of the variables. This omission is probably due to the proprietary nature of the Fair Isaac scorecard. My scorecard is therefore the first analysis to discuss the aggregation procedures and variables used. It also highlights problems that emerge in aggregation of the data when the business is not owner-managed and therefore multiple connections exist owing to the dispersion of ownership among several partners.

The most important finding is that the use of application data alone allows a researcher to derive an application scorecard that is better than chance. However, it is likely that the use of credit bureau data would enhance these scorecards (Chandler and Johnson, 1992). Unfortunately, I was not given access to credit bureau data by the bank. Yet even in the absence of credit bureau data, the scorecards discriminate better than chance between borrowers who default and borrowers who do not.

An additional result of my analysis points to the significance of liquidity in influencing business default. Profit retention variables and gross profit variables are the foremost variables influencing business default rates. The importance of profitability is borne out in the negative correlation between gross profit and default. Furthermore, there is tentative evidence that the levels of retained profits, if indicative of business growth, reinvestment or liquidity, are positively correlated with default.

Table 6.1 Organisation of *'Bigdata930'* and *'SAScard930'*

		Collateral x	Collateral value using *'Bigdata930'*	Collateral value using *'SAScard'*
Business 1	Identifier 1	6,300	6,300	6,750
Business 1	Identifier 2	450		
Business 2	Identifier 1	6,300	6,300	6,300
	Business 2	Identifier 2	6,300	

Table 6.2 'Bigdata930F' **Sum of total borrowing** '*Newsum*'

NSM_BAND(NEWSUM)	LE 4000	LE 10000	LE 40000	LE 100000	GT 100000	Total
Goods	174	123	229	152	112	790
Bads	25	16	47	35	17	140
Total	199	139	276	187	129	930
gij/bij	6.96	7.69	4.87	4.34	6.59	
ln(gij/bij)	1.94	2.04	1.58	1.47	1.89	
Bj/Gj	0.18	0.18	0.18	0.18	0.18	
ln(Bj/Gj)	-1.73	-1.73	-1.73	-1.73	-1.73	
ln(gij/bij) + ln(Bj/Gj)	0.21	0.31	-0.15	-0.26	0.15	

Table 6.3 Sensitivities and specificities for 'Bigdata930F'

	Correct		Incorrect				
Prob. level	At least once grade F	Never grade F	At least once grade F	Never grade F	Correct	Sensitivity	Specificity
0.00	140	0	790	0	15.1	100.0	0.0
0.02	140	6	784	0	15.7	100.0	0.8
0.04	138	46	744	2	19.8	98.6	5.8
0.06	132	123	667	8	27.4	94.3	15.6
0.08	120	231	559	20	37.7	85.7	29.2
0.10	107	321	469	33	46.0	76.4	40.6
0.12	95	396	394	45	52.8	67.9	50.1
0.14	82	472	318	58	59.6	58.6	59.7
0.16	69	524	266	71	63.8	49.3	66.3
0.18	57	573	217	83	67.7	40.7	72.5
0.20	51	617	173	89	71.8	36.4	78.1
0.22	44	653	137	96	74.9	31.4	82.7
0.24	37	677	113	103	76.8	26.4	85.7
0.26	31	702	88	109	78.8	22.1	88.9
0.28	25	715	75	115	79.6	17.9	90.5
0.30	20	732	58	120	80.9	14.3	92.7
0.32	16	741	49	124	81.4	11.4	93.8
0.34	14	751	39	126	82.3	10.0	95.1
0.36	12	763	27	128	83.3	8.6	96.6
0.38	10	768	22	130	83.7	7.1	97.2
0.40	9	770	20	131	83.8	6.4	97.5
0.42	7	773	17	133	83.9	5.0	97.8
0.44	7	776	14	133	84.2	5.0	98.2
0.46	7	781	9	133	84.7	5.0	98.9
0.48	6	784	6	134	84.9	4.3	99.2
0.50	5	785	5	135	84.9	3.6	99.4
0.52	4	788	2	136	85.2	2.9	99.7
0.54	4	789	1	136	85.3	2.9	99.9
0.56	4	789	1	136	85.3	2.9	99.9
0.58	4	790	0	136	85.4	2.9	100.0
0.60	4	790	0	136	85.4	2.9	100.0
0.62	4	790	0	136	85.4	2.9	100.0
0.64	3	790	0	137	85.3	2.1	100.0
0.66	2	790	0	138	85.2	1.4	100.0
0.68	2	790	0	138	85.2	1.4	100.0
0.70	1	790	0	139	85.1	0.7	100.0
0.72	0	790	0	140	84.9	0.0	100.0

-2 Log likelihood Intercept and covariates 718.87

Chi square for covariates 69.102 with 37 DF (p=0.0010)

Table 6.4 Sensitivities and specificities for 'Bigdata930E'

	Correct		Incorrect				
Prob. level	At least grade E	Never grade E	At least grade E	Never grade E	Correct	Sensitivity	Specificity
0.04	278	0	652	0	29.9	100.0	0.0
0.06	276	2	650	2	29.9	99.3	0.3
0.08	276	6	646	2	30.3	99.3	0.9
0.10	275	18	634	3	31.5	98.9	2.8
0.12	270	35	617	8	32.8	97.1	5.4
0.14	265	68	584	13	35.8	95.3	10.4
0.16	250	95	557	28	37.1	89.9	14.6
0.18	245	132	520	33	40.5	88.1	20.2
0.20	229	175	477	49	43.4	82.4	26.8
0.22	212	225	427	66	47.0	76.3	34.5
0.24	202	279	373	76	51.7	72.7	42.8
0.26	183	316	336	95	53.7	65.8	48.5
0.28	169	354	298	109	56.2	60.8	54.3
0.30	156	390	262	122	58.7	56.1	59.8
0.32	143	429	223	135	61.5	51.4	65.8
0.34	127	472	180	151	64.4	45.7	72.4
0.36	115	497	155	163	65.8	41.4	76.2
0.38	99	525	127	179	67.1	35.6	80.5
0.40	87	548	104	191	68.3	31.3	84.0
0.42	74	568	84	204	69.0	26.6	87.1
0.44	65	579	73	213	69.2	23.4	88.8
0.46	56	590	62	222	69.5	20.1	90.5
0.48	44	608	44	234	70.1	15.8	93.3
0.50	34	616	36	244	69.9	12.2	94.5
0.52	28	622	30	250	69.9	10.1	95.4
0.54	22	623	29	256	69.4	7.9	95.6
0.56	18	630	22	260	69.7	6.5	96.6
0.58	18	637	15	260	70.4	6.5	97.7
0.60	14	640	12	264	70.3	5.0	98.2
0.62	10	645	7	268	70.4	3.6	98.9
0.64	8	647	5	270	70.4	2.9	99.2
0.66	7	647	5	271	70.3	2.5	99.2
0.68	5	649	3	273	70.3	1.8	99.5
0.70	4	650	2	274	70.3	1.4	99.7
0.72	2	650	2	276	70.1	0.7	99.7
0.74	2	650	2	276	70.1	0.7	99.7
0.76	1	652	0	277	70.2	0.4	100.0
0.78	0	652	0	278	70.1	0	100.0

-2 Log likelihood Intercept and covariates 1057.499

Chi square for covariates 77.009 with 37 DF (p=0.0002)

Table 6.5 **'Bigdata930F'; classification at 0.50 cut-off**			
	Predicted bads	Predicted goods	Total
At least F grade	5	135	140
Never F grade	5	785	790
			930

Table 6.6 **'*Bigdata930E*'; classification at 0.50 cut-off**			
	Pred. bads	Pred. goods	Total
At least *E* grade	34	244	278
Never *E* grade	36	616	652
			930

Table 6.7 Gini coefficients for all scorecards Gini coefficients (c)

	(1) **Ex post validation** 70 percent training sample	**(2)** **Out-of-sample validation** 30 percent holdout sample	**(3)** **Lachenbruch**
'DrasticE'	0.75	0.51	0.58
'DrasticF'	0.81	0.57	0.59
'Bigdata1572E'	0.65	0.57	0.57
'Bigdata1572F'	0.68	0.56	0.55
'Bigdata930E'	0.71	0.55	0.59
'Bigdata930F'	0.73	0.60	0.59
'SAScard930E'	0.66	0.62	0.44
'SAScard930F'	0.71	0.57	0.43

Table 6.8 Variable names used in '*Bigdata930F*' scorecard

Aclgroup	Account credit limit	*Pgpgroup*	Present gross profit
Agegroup	Entrepreneur's age	*Pjsgroup*	Projected sales
Agrgroup	Aggregate borrowings	*Pnpgroup*	Present net profit
Blngroup	Has a business loan	*Psdgroup*	Present business drawings
Bpvgroup	Present value of bank owned asset (mortgaged asset)	*Pstgroup*	Past sales turnover
Bsmgroup	Number of miles business is from bank	*Rgpgroup*	Recent gross profit
Cprgroup	Breakdown between cash sales and credit sales	*Rplgroup*	Recent profit and loss balance
Dyigroup	Number of years work experience	*Rrpgroup*	Recent retained profit
Ldogroup	Business premises leased or owned	*Rtagroup*	Recent total assets
Nbgroup	Owner has contributed own equity	*Rtngroup*	Retained profit
Nsmgroup	New amount borrowed	*Ryegroup*	Had financial accounts
Olngroup	Has multiple loan facilities	*Singroup*	Sales increase
		Taggroup	Total aggregate borrowings

Table 6.9 Significant variables in the '*Bigdata930F*' model before testing for collinearity

Weight of evidence variable name	Pr > chi-square
Intercept	0.00
*Cprgroup***	0.02
*Taggroup***	0.02
*Ryegroup***	0.03
*Dprgroup***	0.03
*Bpvgroup***	0.04
*Rtngroup**	0.07
*Pstgroup**	0.08
*Rtagroup**	0.09
*Ldogroup**	0.09
*Rgpgroup**	0.10

*** significant at the 1-percent level; ** significant at the 5-percent level; * significant at the 10-percent level

Table 6.10 Significant variables in the *'Bigdata930F'* model after testing for collinearity

Weight of evidence variable name	Pr > chi-square
Intercept	0.00
*Cprgroup****	0.01
*Rrpgroup***	0.06
*Rgpgroup**	0.08
*Rtngroup**	0.08
*Ldogroup**	0.09

*** significant at the 1-percent level; ** significant at the 5-percent level; * significant at the 10-percent level

Figure 6.1 Derivation of different scorecard estimation samples

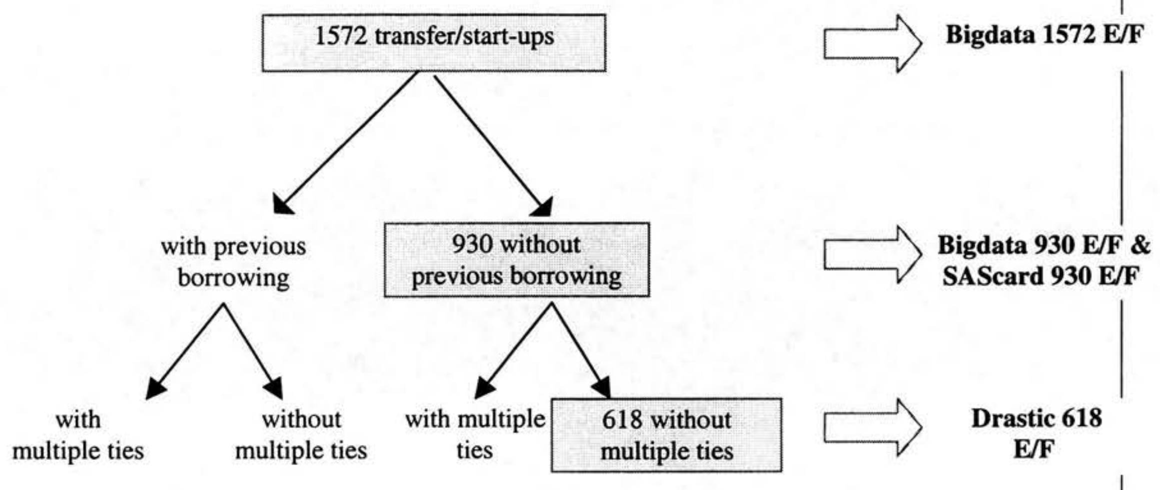

Figure 6.2 Plan for creation of 'drastic' **dataset**

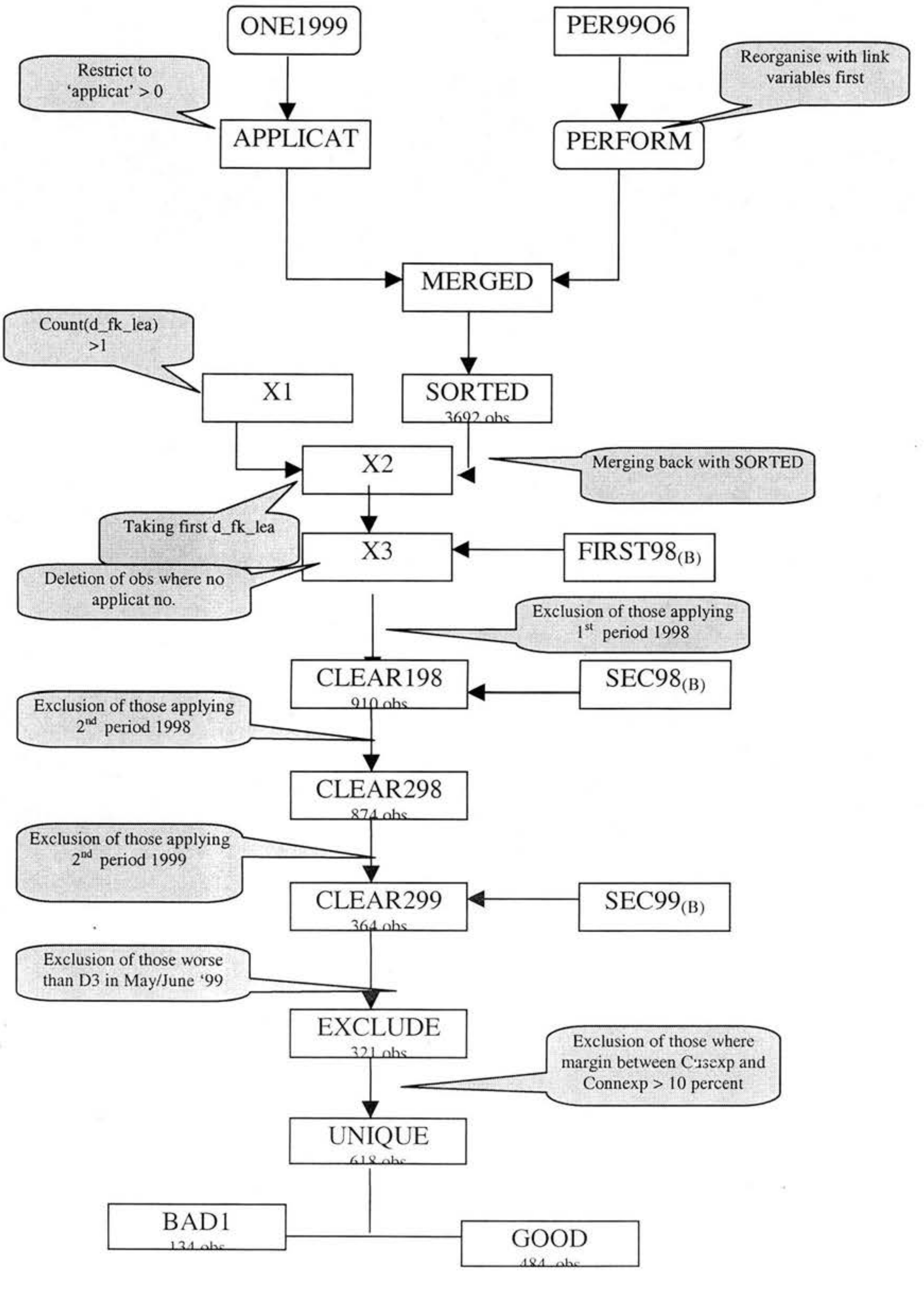

Figure 6.3 Diagram of the timeline

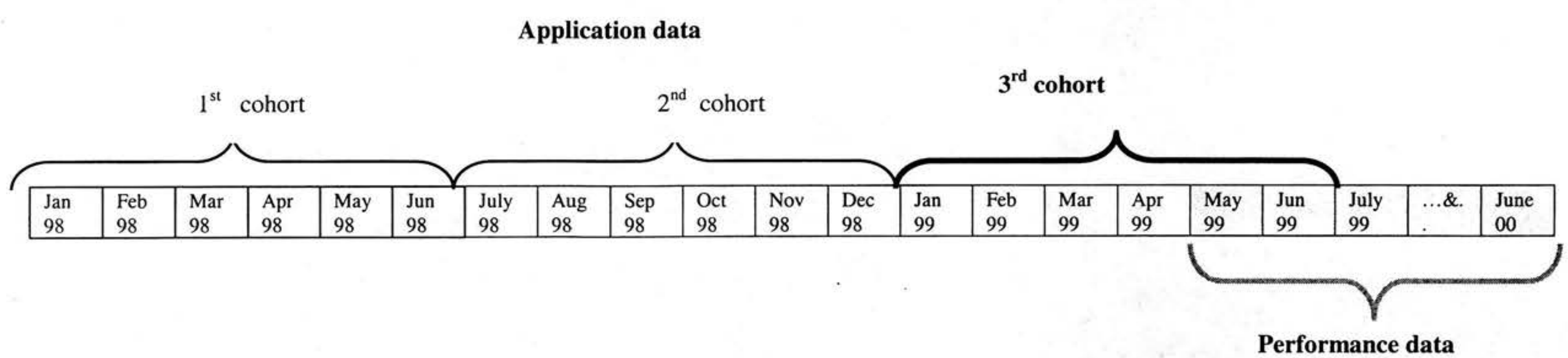

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Figure 6.4 WOE Categories for 'proj_sal' Bigdata930E

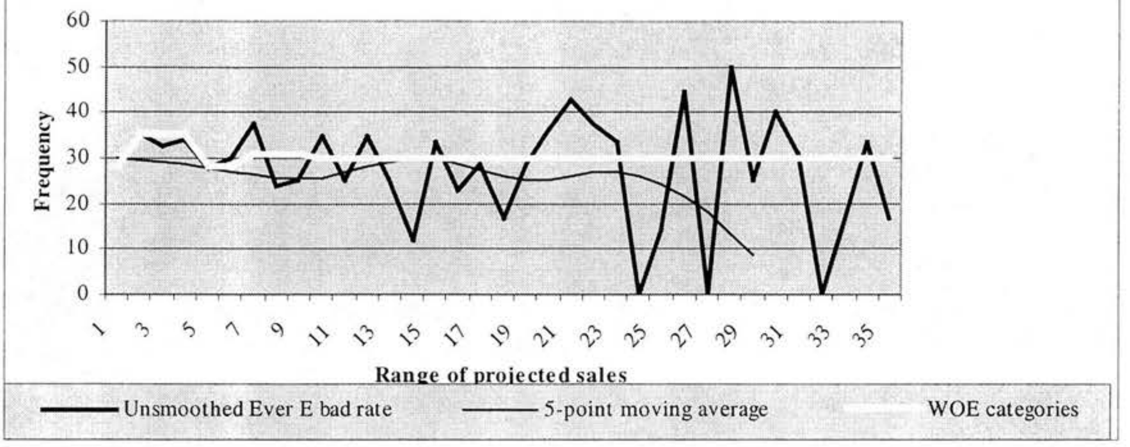


Figure 6.5 WOE Categories for 'proj_sal' Bigdata930F

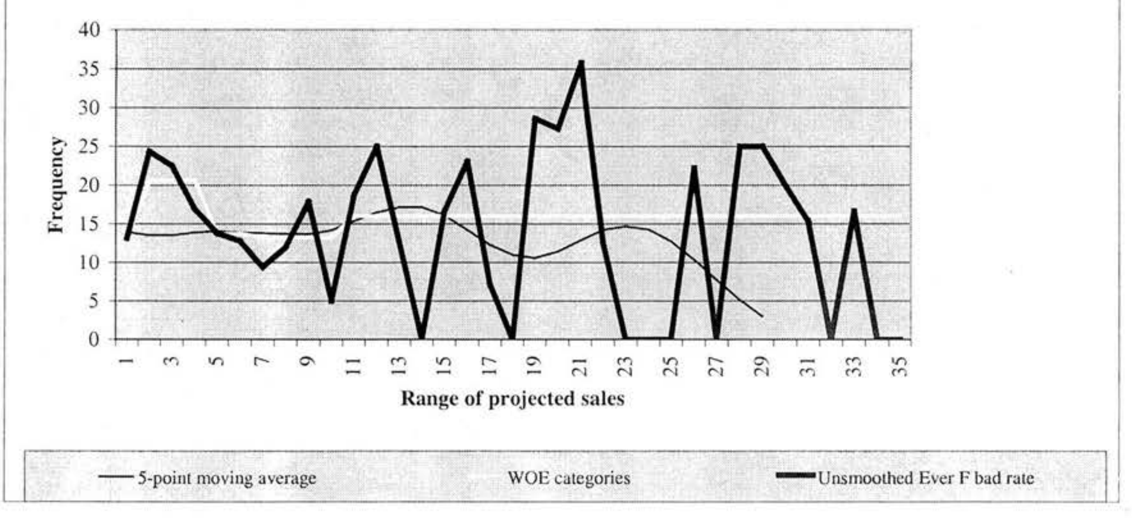


Figure 6.6 **Predicted probabilities for '*Bigdata 930E*'**

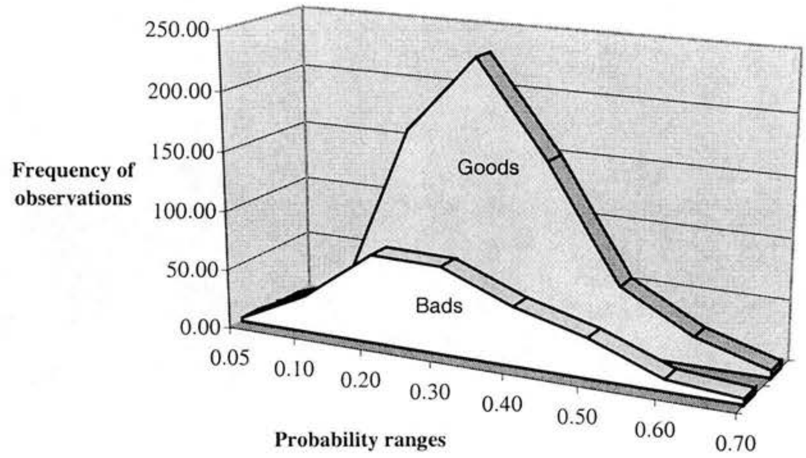


Figure 6.7 **Predicted probabilities for *'Bigdata930F'***

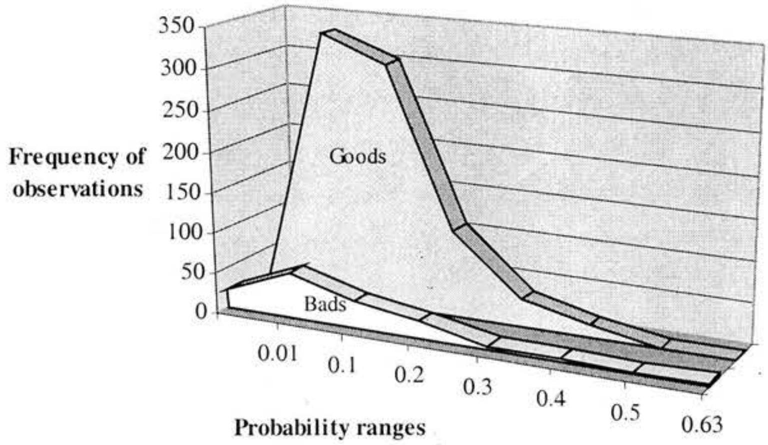


Figure 6.8 ROC curve for Bigdata930E

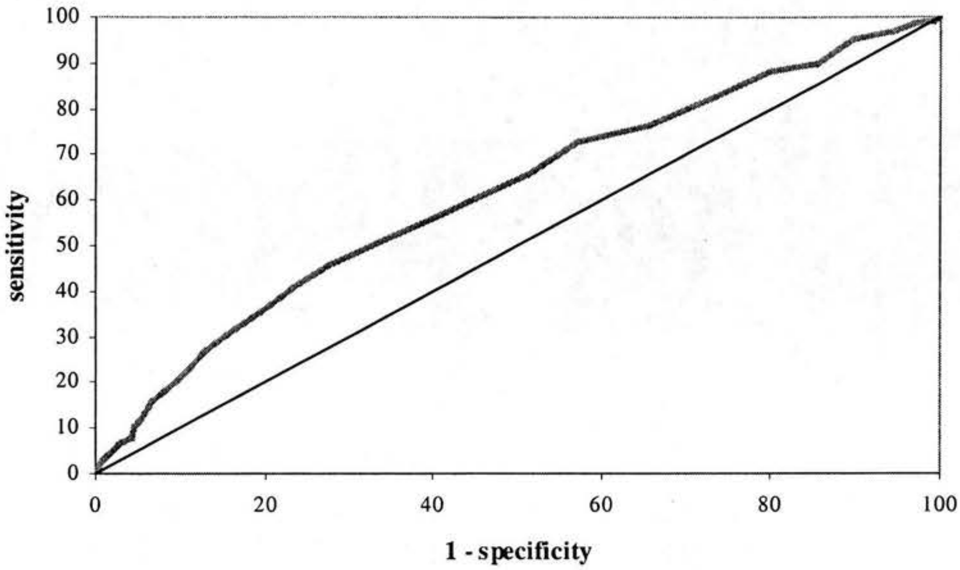


Figure 6.8 ROC curve for Bigdata930F

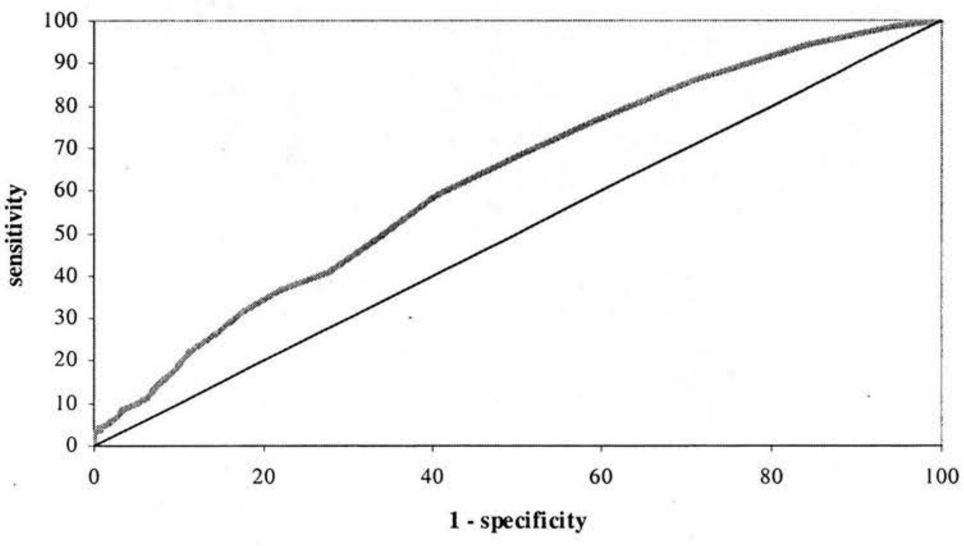


Table 6.10 ROC for Bigdata930F and Bigdata1572F

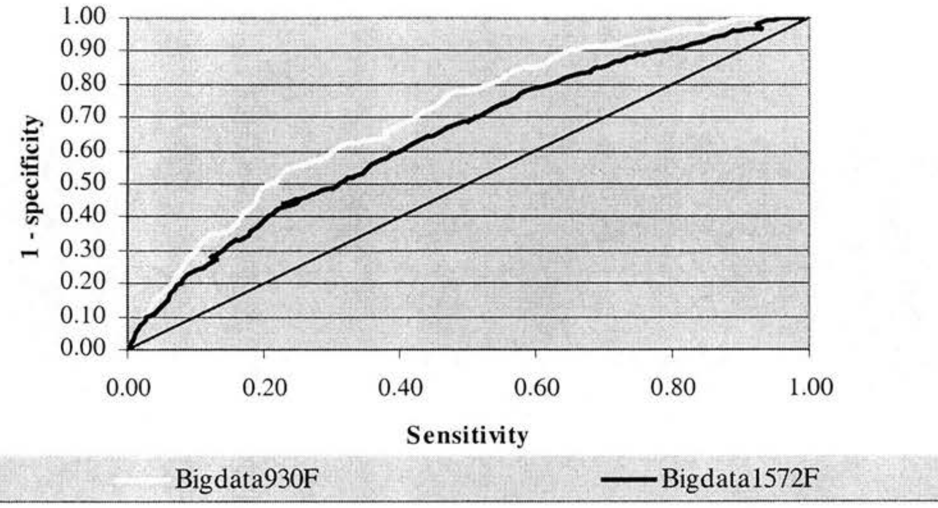


Figure 6.11 ROC curve for BigdataF and BigdataE

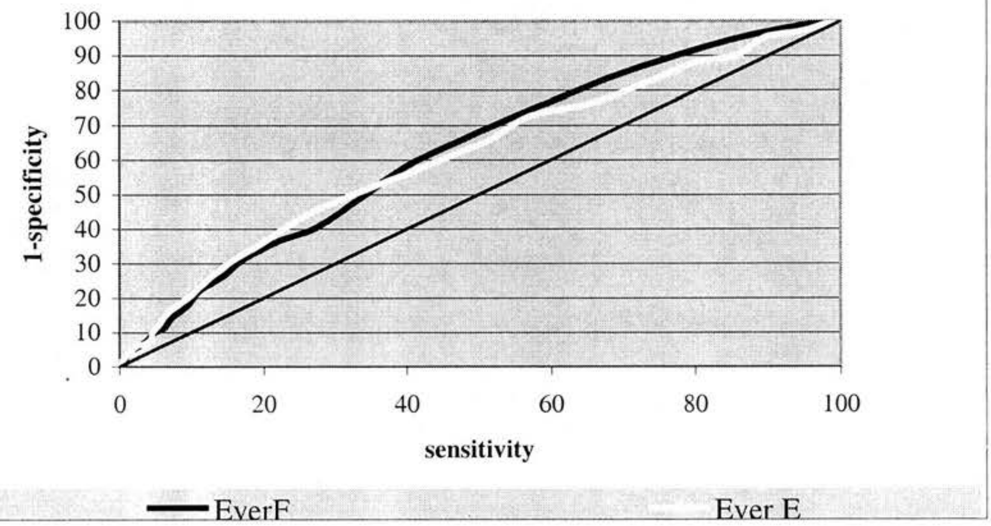


Figure 6.12 WOE for '*cprgroup*'

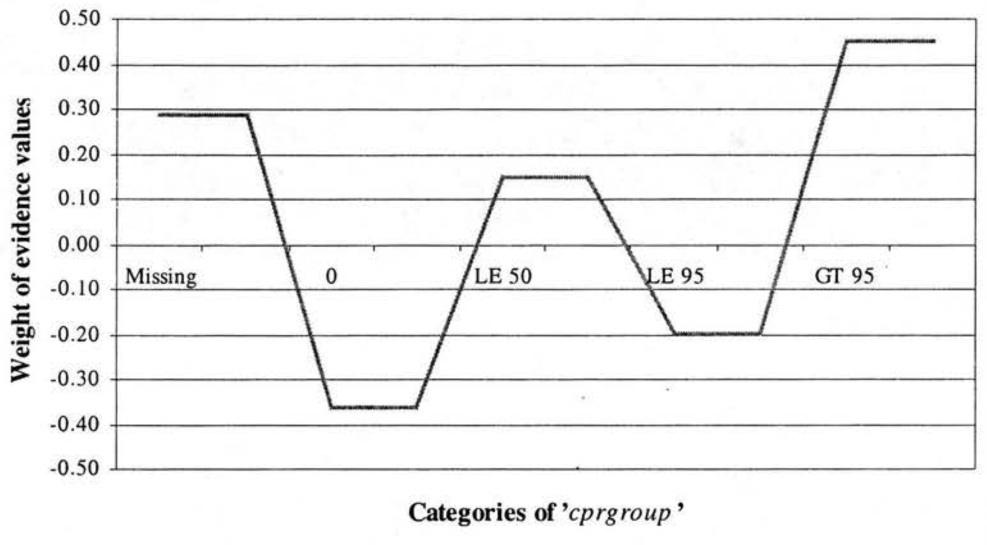


Figure 6.13 WOE for '*rrpgroup*'

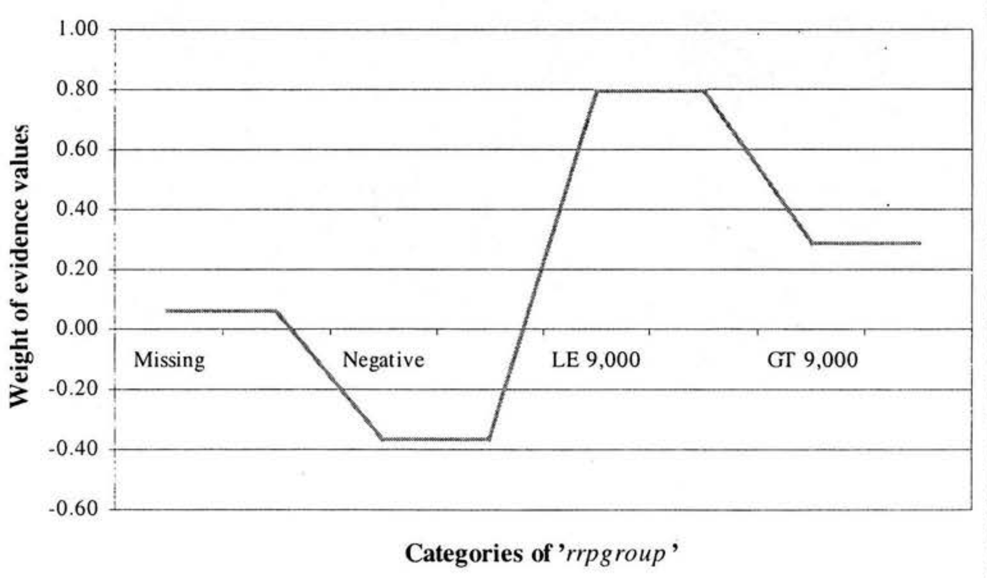


Figure 6.14 WOE for '*rgpgroup*'

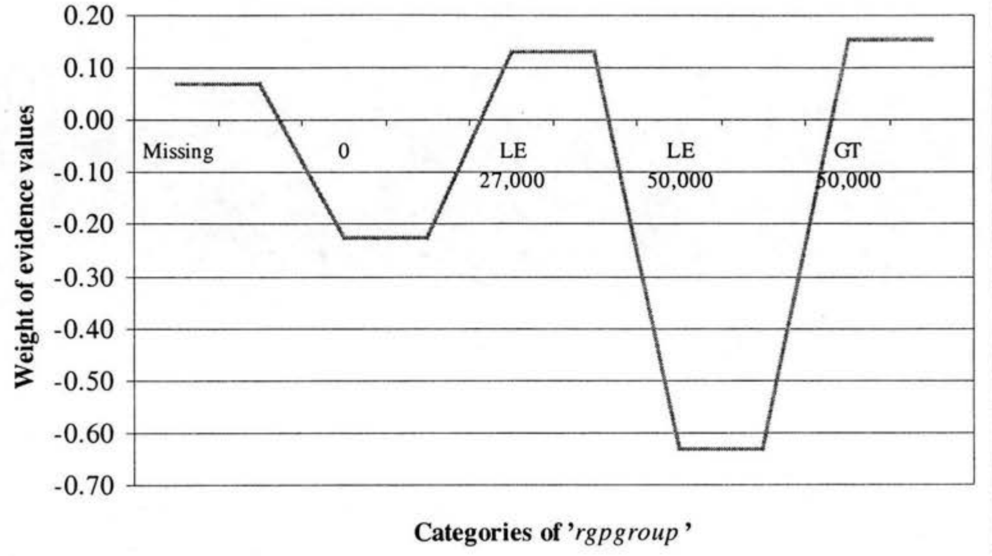


Figure 6.15 WOE for '*rtngroup*'

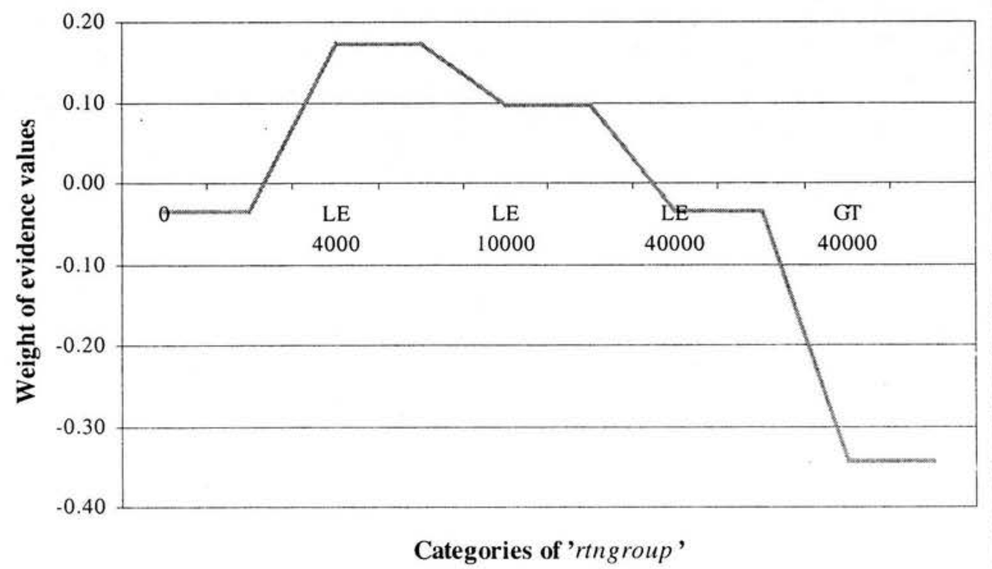
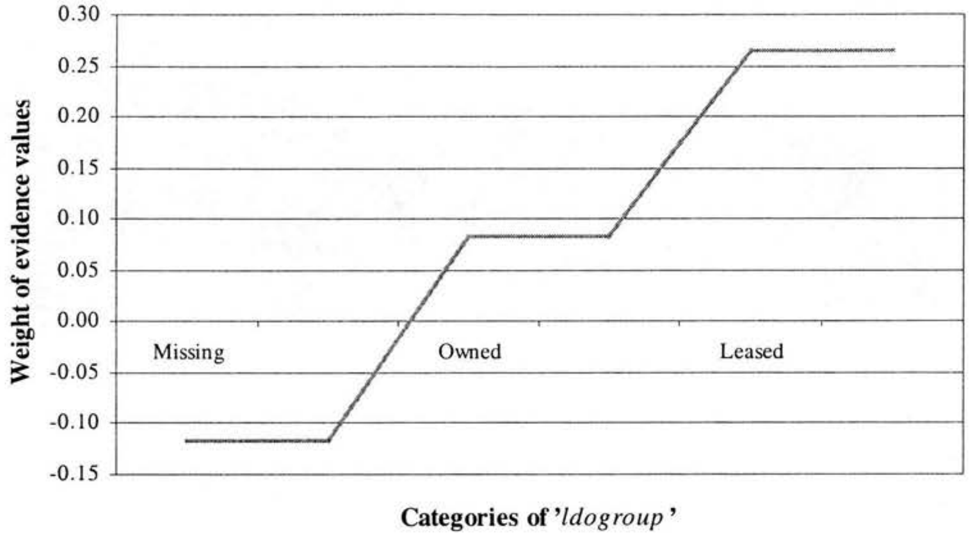


Figure 6.16 WOE for *'ldogroup'*



Chapter 7

Impact of *entrepreneur-bank* relationships on the price of credit

7.1 Introduction

The aim of this chapter is to investigate the role played by *entrepreneur-bank* relationships in influencing the cost of credit. An *entrepreneur-bank* relationship is a pre-existing relationship that exists prior to the time in which the entrepreneur applies for this first business loan with the bank.

No existing analysis has yet explored the impact of pre-existing *entrepreneur-bank* relationships on the cost of first-period business borrowing. However, there is a closely related literature on the effects of borrower reputation on the price and other terms of credit such as collateral (Petersen and Rajan, 1994; Berger and Udell, 1995). The model by Petersen and Rajan (1995) that borrows from Diamond (1989) and that illustrates the effect of close business-bank ties, has already been outlined in **section 2.4** of **Chapter 2**. I will refer to this parallel literature on borrower reputation and interpret the findings of my analysis of *entrepreneur-bank* relationships in the context of this wider literature. A full description and critique of these *borrower reputation* models is provided in **section 2.5** of **Chapter 2**.

7.2 The structure of this chapter and its contribution to the credit pricing literature

In this chapter I seek to establish whether the presence of pre-existing, *entrepreneur-bank* relationships influence the cost of first-time business finance using a unique, UK dataset of loans to first-period business borrowers. In so doing, I appeal to theories of private information and the effect of reputation on the cost of borrowing. I expect that any differences in my results compared with previous studies that proxy reputation using *business-bank relationships*, will be due to differences in the magnitude of the effect of reputation, rather than in the direction of the effect. This is because I have chosen to examine small businesses when the business-bank relationship commences and private-information effects are likely to be most pronounced, hence reputation is predicted to play a pivotal role due to the early-stage nature of borrowing in my data.

I also compare the contribution of reputation and credit history variables (non-observable, private information variables) with observable, human capital variables in explaining the price of credit after controlling for variables describing the amount borrowed, loan type, purpose and security.

My first research question aims to establish whether the previous borrowings of an entrepreneur prior to his take-up of a commercial loan, in other words, his *entrepreneur-bank* relationship, influence the price of his credit.

The second research question that I address concerns the incremental value of firm/borrower quality variables (observable factors) compared with loan contract variables in explaining the price of credit. If the bank is motivated by transaction variables, the explanatory power of loan contract variables as a group should be higher than that of the firm quality variables.

I include additional variables in the group of firm quality variables that have not been used before in past studies of this kind. For example, the number of years employment experience the entrepreneur has, whether the entrepreneur is confident of his future and whether the business can continue to operate without the business owner.

My analysis additionally contains a more exhaustive range of loan contract variables compared to the range employed in previous research. The choice of loan contract variables used in my estimations includes the amount borrowed and the value of collateral. This is the first study relating to the price of credit which is able to show the trade-off between the price of credit (interest margin) and collateral level, if such a trade-off exists. My study is also the first of its kind to use the amount borrowed as an explanatory variable. This latter addition is necessary on the grounds that the per unit cost of credit is hypothesised to be decreasing in the amount borrowed. In other words, if transaction and monitoring costs are reduced on larger credit volumes, then the amount borrowed is an essential explanatory variable for the interest margins. By exploring the sensitivity of interest margins to the volume of credit, my analysis is the first to indirectly examine the phenomenon of interest rate 'embeddedness' described by Petersen and Rajan (1994) by including the amount borrowed as an additional explanatory variable[1].

I structure this chapter as follows. In the next section, I explain why it is necessary to explore *entrepreneur-bank* relationships. In the section following this, I describe the major theoretical and empirical contributions to this area. The section following this describes my data, which will be used in the estimations that follow. I then introduce the variables used to estimate the price of credit. Next I present some descriptive statistics and the results of my regressions. In the final section, I conclude whether *entrepreneur-bank* relationships affect the price of credit after controlling for other variables that are likely to influence credit terms.

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[1] Interest rate 'embeddedness' is described more fully in **section 7.4**

7.3 Why investigate the influence of *entrepreneur-bank* relationships?

Numerous theoretical and financial economists have investigated the price of commercial credit. Central to the price of credit is the role of business-bank relationships because these are argued to influence the costs of lending to unquoted small businesses where the problem of information asymmetry is most acute. Several empirical studies have sought to establish the impact of borrower reputation on numerous aspects of business credit. Issues where relationships are shown to play a role include credit availability, the pricing of IPOs (initial public offerings) and the magnitude of interest on various types of borrowing (Cole, 1998; James and Weir, 1990; Berger and Udell, 1995; Petersen and Rajan, 1994). The aim of my chapter is to investigate whether the presence of pre-existing *entrepreneur-bank* relationships influence the cost of first time business finance.

The founder of a business start-up has often established a credit history (*entrepreneur-bank* relationship) prior to setting up his business. An *entrepreneur-bank* relationship therefore predates a business-bank relationship because it is the only known relationship in existence when an entrepreneur sets up a new business and when costless public information about the business is non-existent.

A lender can amass information about borrowers over a series of consumer products such as home mortgages, credit cards, car and education loans or personal overdrafts. Pre-existing *entrepreneur-bank* relationships are hypothesised, to influence the cost of any subsequent loans to borrowers, including any first-period business loans. Practitioners who estimate small business application scorecards are cognisant of the interconnectedness between entrepreneurs' personal finances and their business risk and include credit bureau data relating to business principals in scorecard estimations (Asch, 1995). If an entrepreneur has shown himself to be a reliable bank customer in the past, there is little reason to believe that he will alter his future behaviour. However, an element of uncertainty is inherent in all new ventures (project risk), irrespective of the entrepreneur's reliability (customer risk). Holding project risk constant, if a bank is responsive to customer risk, it should adjust interest margins to reflect changes in the customer's risk profile.

However, the intuitive expectation that a bank having an *entrepreneur-bank* relationship will be lenient to its business client by charging a lower interest margin on the client's first-period business loan, is not necessarily realistic. There is an argument to support the reverse case that a bank <u>raises rather than lowers</u> the interest margin. If a borrower is tied to his original lender due to the effect of private information where other potential lenders cannot observe the borrower's reputation, little choice remains to an entrepreneur but to seek finance from his original lender who is aware of his reputation. An entrepreneur may be required to pay higher-than-competitive interest margins on his borrowings in subsequent lending periods because he is *'informationally captured'* by his lender (Sharpe, 1990). Even if other banks wanted to attract *'informationally captured'* borrowers, they would run the risk of adverse selection. Competing banks may suspect that the borrower's departure is prompted by the original lender's refusal to expand or to re-extend the borrower's original loan facility, due to poor repayment behaviour. If the bank is able to wield this type of market power, the credit market is understood to be 'concentrated' (Petersen and Rajan, 1995).

Therefore, if private information best describes the information environment surrounding a first-period business loan, a bank with an *entrepreneur-bank* relationship extending over a number of years is in a better position, than a competitor bank with no such relationship, to assess the integrity or creditworthiness of this new business borrower. This is because borrower risk is conditioned on past lending experience with the borrower (Diamond, 1991). If the market for first-time loans is conditioned on private information, we should see considerable emphasis placed on variables that are non-observable to outside banks i.e. reputation and credit history as determinants of the interest rate charged[2]. On the other hand, if emphasis is placed on observable characteristics of the borrower, such as his age or work experience, support for private information arguments is weakened. It is important when drawing this distinction between observable and non-observable variables influencing the cost of credit, that a researcher controls for the variables collateral, borrowed amount, loan purpose and type i.e. the transaction-cost variables[3].

In this chapter I assume that only the original lender is aware of a borrower's reputation at the business start-up stage. Newly founded UK businesses are unlikely to have audited, public or comprehensive accounts (Gower, 1992). Additionally, they are highly unlikely to exhibit share valuations unless they emanate from a larger, established parent company. The age of a business is known to convey information about a borrower's creditworthiness to outsiders and denotes the true quality of a business borrower (Diamond, 1989). However, at

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[2] Assuming that accessing a borrower's credit history implies a cost. Diamond (1989) refers to a borrower's credit history as an observable commodity. We argue that borrower credit histories can be accessed via credit bureau but that it is a source of information that must be purchased and therefore is not equivalent to the 'costless' information arising from an *entrepreneur-bank* relationship.

[3] Particular caution must be taken in interpreting the results of any analysis if assets and borrower type are correlated (James and Weir, 1990; Cressy, 1996b). However, if one assumes that first-period business borrowers post all their assets as collateral (a plausible assumption given initial wealth constraints) and collateral is included as an explanatory variable, there is less danger of model misspecification.

the start-up stage, business age is zero and therefore no costless source of information about the borrower exists[4].

I argue that in empirical investigations of the determinants of interest margins there is an advantage in using *entrepreneur-bank* relationships rather than business-bank relationships to proxy reputation effects. This arises because by the time a business successfully applies for a rollover loan, the borrower is already likely to have established a public credit history. It follows that the entrepreneur is freer to move his custom to another bank once his survival can be observed. Once the first critical five years of a new firm's trading life have elapsed, external investors are likely to regard a business more favourably[5]. Therefore, the impact of reputation should be most pronounced when an entrepreneur takes out his first-period business loan[6].

In a parallel literature on the effects of reputation for publicly traded companies, studies have found that the *renewal* of a loan facility rather than *new issue* of a loan facility often generates comparatively higher market returns (Lummer and McConnell, 1989; Best and Zhang, 1993). This difference in returns arises from the positive signal conveyed to investors when a bank extends its loan commitment to subsequent periods. James and Weir (1990) find that the existence of a borrowing relationship alone is sufficient to reduce uncertainty regarding the value of an initial public offering (IPO) while James (1987) finds that that investors react positively to the announcement of new bank credit facilities.

In view of the diminishing importance of private-information over time, (or following the first rollover loan) by using *entrepreneur-bank* relationships to proxy reputation effects on the price of credit, I expect to capture the effect of borrower reputation on interest margins at the earliest possible stage in a firm's development. At this stage, the reputation of the borrower is expected to matter most because at this time there is the least amount of public information about the borrower.

7.4 The literature on borrower reputation and the price of credit

The literature that predicts the effect that business-bank relationships have on the price of credit is divided into two opposing viewpoints. Some models predict that in the first borrowing period interest rates will be lower than in the second borrowing period

[4] We assume that credit bureau data is not costless.

[5] The high attrition rates exhibited by new businesses is evidenced by a 20 percent failure rate for UK start-up businesses in their first trading year, with 60 percent of businesses failing by their fifth trading year (Barclay's Bank Information Service, 2000. *http:/www.businesspark.barclays.com*)

[6] Petersen and Rajan (1994) found that the role of reputation is strongest when firms are young and that the marginal returns to reputation decrease as a firm ages.

(Greenbaum et al, 1989; Sharpe, 1990). On the other hand, Boot and Thakor (1994) and Diamond (1989) have developed models predicting completely the opposite effect on interest rates, whereby a bank commences lending at a comparatively higher rate than in subsequent periods. Furthermore, Petersen and Rajan (1995) have developed a model that delivers different predictions, describing the disparity between first-period and second-period interest margins, that are contingent on the degree of competition/concentration in the credit market.

Perhaps these differences in model predictions arise from the different emphasis of each model with implications for what happens to the price of credit when the first borrowing period elapses. For example, Sharpe focuses on implicit contracts as a way of cementing the borrower-bank relationship. Petersen and Rajan deal primarily with bank concentration as a driver of the inefficiencies arising from private information. Greenbaum et al. deal with, among other issues, the exit costs that would be incurred by a second-period borrower. Boot and Thakor assume that lending takes the form of a sequential game with the prospect of cheaper second-period finance operating as a deterrent to borrowers hoping to leave their original lender. Diamond assumes a multiperiod framework entailing a game where it only pays a borrower to develop a reputation once a borrower has survived the first period of borrowing with high interest rates.

These models, with the exception of Diamond, all assume that private information collected by the bank about the borrower's creditworthiness cannot be passed on to other lenders[7]. The different predictions of models for interest rate margins are summarised in **Table 7.2**.

Relatively little empirical work dealing with the effect of reputation on the price of credit to small firms has been carried out. This is due to difficulties in obtaining in-house data from retail banks on non-quoted small businesses. All existing empirical work on small businesses uses data from the US National Survey of Small Business Finances (NSSBF). Thus Cole (1998), using data from the 1993 NSSBF, finds that pre-existing business-bank relationships enhance the borrower's prospects of obtaining credit. Petersen and Rajan (1994) find that the duration of a pre-existing business-bank relationship increases credit availability but that the duration of a relationship exerts no significant effect on the price of credit. Berger and Udell (1995) find that borrowers with longer business-bank relationships are associated with comparatively lower margins on their Letters of Credit (L/C's) facilities. The disparity between the results obtained by Berger and Udell (1995) and Petersen and

[7] Diamond (1989) cites the availability of a borrower's credit rating as confirmation that a borrower develops a public reputation

Rajan (1994) is most likely due to the relationship-driven, rather than transaction-driven nature of L/C's.

In a separate analysis, Petersen and Rajan (1995) find that older firms (age being a proxy for external reputation effects) are associated with lower interest rates, irrespective of the structure of the credit market. They find that lenders tend to smooth the cost of credit over the life cycle of the firm in a concentrated market, and so the decline in interest margin with firm age is less dramatic in concentrated, compared to competitive, markets. Lenders appear to charge lower-than-competitive interest rates when a firm is young but recoup this shortfall when the firm is older by charging higher-than-competitive interest rates.

Overall, this literature suggests that business-bank relationships (private information) are likely to matter most when the financial product is relationship-driven e.g. L/Cs. In addition, if markets are concentrated, a lender will amortise the costs of low initial interest rates to first-term borrowers by recouping the initial outlay over subsequent loans[8]. Therefore, while the costs of borrowing are expected to decrease over the firm's life cycle, the decrease in the cost of borrowing may be less than the decrease warranted by the overall reduction in risk. Therefore, the overall effect of close firm-creditor ties on the cost of borrowing is ambiguous (Petersen and Rajan, 1994).

Moreover, Petersen and Rajan (1994) concluded that the 'embeddedness' of interest rates makes the role of business/bank relationships redundant. 'Embeddedness' means that the sanctioner has little discretion over the magnitude of the interest margin because the volume, rather than the risk, of credit determines interest margins. Hence, a sanctioner has discretion over how much he lends to a business borrower but little discretion over the interest margin, since this is determined by the magnitude of the loan. If interest rates are embedded in the size of loans, they should respond more to changes in the volume of borrowing than to changes in other explanatory variables, such as relationship or borrower quality variables. With embeddedness, there is little latitude for the person sanctioning the loan to consider such 'soft information' as borrower quality.

7.5 The dataset and description of the variables

The data used contains 5,967 small businesses that had no previous commercial loan with the bank. The vast majority of these first-period borrowers were in the form of business start-ups although sources at the bank indicated that several first-period borrowers had

[8] A feature of private information is that it tends to concentrate the market for credit because borrowers are dependent on their original lender and hence private information promotes the existence of exclusive business-bank relationships.

transferred their custom from another bank[9]. All data related to loans or overdrafts from my UK bank data source and related to the borrowing period December 1997 to July 1999.

Regarding the composition of small businesses in my data, none of these small businesses was incorporated because publicly traded businesses were dealt with by a separate, less automated branch of the bank. The majority of the small businesses, approximately 80 percent, are sole traders (owner managed) with unlimited liability. About 19 percent are partnerships, with a further 1 percent of the sample enjoying limited liability status. I derived this approximation for the breakdown of the companies in my sample by inferring that personal guarantees are supplied by limited companies and that the presence of partners suggests a non-owner managed business. Unfortunately, no better approximation of the breakdown of my data is available.

A list and description of the variables used in this analysis is contained in **Table 7.1**.

I estimated an ordinary least squares (OLS) regression for the effect of the five explanatory variable groups on the magnitude of the interest margin charged by the bank. It takes the form;

$$Y_i = \alpha + \sum_{j=1}^{1} \beta_j x_{ij} + \sum_{j=2}^{6} \beta_j x_{ij} + \sum_{j=7}^{7} \beta_j x_{ij} + \sum_{j=8}^{15} \beta_j x_{ij} + \sum_{j=16}^{18} \beta_j x_{ij}$$

Where

Y_i is the magnitude of the interest margin for borrower i

$_{j=1}$ is my relationship proxy

$_{j=2-6}$ represent my loan contract variables

$_{j=7}$ is my size proxy

$_{j=8-15}$ are borrower/business characteristics

$_{j=16-18}$ are risk variables

The subscript i refers to the number of borrower observations and the subscript j refers to the explanatory variables. I explore whether the cost of credit, in terms of interest margins, is positively or negatively related to the magnitude of first period borrowing for entrepreneurs with or without an *entrepreneur-bank* relationship.

I use the dummy variable *'prevbor=1'* to denote whether a borrower has previously borrowed or not[10]. This is consistent with multiperiod lending dummies used in other research (Lummer and McConnell, 1989; Best and Zhang, 1993).

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[9] Unfortunately, there was no way of differentiating between the two types of first-period borrower although I was assured by sources at the bank that the number of businesses that had transferred from another bank were comparatively few. The literature on adverse selection (see **Chapter 2** section **2.2**)

The loan contract variables that I use are as follows: the variable *'borr'* indicates the amount borrowed, *'coll'* indicates the amount of collateral used, *'overdrft'* denotes whether the loan is an overdraft or not, *'working'* signifies whether the loan is for working capital purposes and *'nonborr1'* indicates that the borrower injected his own cash savings into the project. I also include the squared terms of the continuous variables in this set of loan contract variables. These are squared borrowing, *'borr2'*, and *'coll2'* denoting squared collateral.

The reason that I use these loan contract variables is that the amount borrowed and the level of security or collateral define the level of exposure of the bank to the business. These two variables have not been used before in the two existing studies by Petersen and Rajan (1994) and Berger and Udell (1995). The reason for this omission of these two loan contract variables in previous research is that they are possibly difficult to estimate when borrowing is cumulative or when it has been partially amortised. Because all the loans in my data refer to first-period business borrowing, these variables are available. I would expect an inverse relationship between collateral and interest margins. This trade-off between interest margins and the level of collateral should be evidenced by a negative sign for the collateral variable *'coll'*. I would expect that higher amounts of borrowing indicated by higher values for the borrowing variable *'borr'* should be associated with lower margins due to the reduced per unit transaction-cost of lending comparatively larger amounts of finance.

The variables relating to the term structure of the loan are the overdraft *'overdrft'* and working capital *'working'* dummies. An overdraft dummy has been used before in previous work where Petersen and Rajan (1994) differentiated between loans and overdrafts. Berger and Udell (1995) directly controlled for the structure of the loan by concentrating only on the subset of all borrowers who had taken out an overdraft[11]. I would expect both overdraft and working finance to be associated with higher interest margins (a positive sign). My rationale for a positive sign for the variables *'overdrft'* and *'working'* is due to the higher risk associated with an option to buy money forward at a fixed rate of interest in order to fund the working capital requirements of the business (Berger and Udell, 1995).

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confirms that a bank is less likely to accept a business who has previously borrowed from another bank on the grounds that the original lender is unhappy with the borrower's repayment record or risk profile

[10] An example of an *entrepreneur-bank* relationship is where an entrepreneur had a mortgage with the bank before taking out a business loan. The bank therefore infers the borrower's creditworthiness from his repayment performance on the mortgage. However, the bank still remains unsure how the entrepreneur will manage his business and has no pre-existing business-bank relationship. Therefore, no business in my sample had a business-bank (as opposed to *entrepreneur-bank*) relationship before applying for its first loan.

[11] Berger and Udell (1995) actually deal with Letters of Credit which are analogous to overdrafts. L/C appears to be the preferred US terminology for overdraft finance.

A size proxy is possibly not as relevant to my analysis as to analyses containing firms that greatly vary in size. However, in order to keep my analysis consistent with similar US analyses, I control for size. Hence US analyses using data from the NSSBF survey control for size (Petersen and Rajan, 1994; Berger and Udell, 1995). Although, as I have noted in **footnote 9** that very few businesses in my sample have transferred from another bank due to the likelihood of adverse selection, in order to control for any size differences that the presence of transferred businesses might give rise to, I decided to control for variation in industry size. This variable therefore captures any variation in interest margin that is due to a business being comparatively larger, or more established, than other businesses.

I furthermore control for human capital variables in view of the importance placed on these variables by Cressy (1996c) The human capital variables included in this analysis are as follows: borrower age, *'age'*, the number of years work experience that the entrepreneur has, *'exp'*, whether the entrepreneur thinks his business is risky, *'norisk'*, whether the entrepreneur has a business partner, *'partner'*, whether the borrower retained a profit from his previous business sales, *'retain1'*, and whether the business can continue in the absence of the business principal, *'busoper'*. I would expect more mature borrowers with longer work experience records to receive lower interest margins than young borrowers who have not gained much work experience. Such borrowers are expected to have accumulated more experience on how to derive and implement a viable business project. Hence a negative sign is predicted for the variables *'age'* and *'exp'* with interest margin. I included both the variables *'age'* and work experience *'exp'* although there is likely to be a very high correlation between them. Indeed, the Pearson correlation between them of 0.417, is significant to the 1 percent level. The reason I include both variables is to allow for the fact that professionals who enter self-employment, such as doctors and lawyers, are likely to have spent more time in full time education and have less work experience than their age would suggest, than an early school leaver. I would also expect the variables *'partner'* and *'busoper'* to be associated with lower interest rates and hence a negative sign because entrepreneurs with business partners benefit from shared knowledge and decision making as well as additional equity sources. Furthermore, a business that can continue to operate when the principal owner is sick or otherwise absent, is assured of a more steady and continuous income stream. Hence, businesses with fewer succession issues (*'busoper'*=1) are expected to receive lower interest margins.

I also control for the business risk variables *'debtres'* and *'anyinso'*. The variable *'debtres'* indicates whether the business owner had had his borrowing consolidated or rescheduled in the past. The variable *'anyinso'* indicates whether the borrower was insolvent at any stage in the past prior to obtaining the loan. These variables being symptomatic of financial distress are predicted to be positively related to interest rates where borrowers exhibiting past financial distress are predicted to receive higher interest margins. This reasoning is consistent with the results obtained by Petersen and Rajan (1994) and Berger and Udell (1995) where past insolvency was positively related to the price of credit.

7.6 Descriptive statistics for the data

I first of all explore some simple descriptive statistics describing the breakdown of our variables according to whether an *entrepreneur-bank* relationship exists or not. 1,152 of the 5,968 borrowers in our data have *entrepreneur-bank* relationships compared with 4,816 through-the-door applicants. It would appear that there are more through-the-door applicants than borrowers who are known beforehand to the bank.

Table 7.3 shows the composition of interest margin, *'interest'*, amount borrowed, *'borr'*, the number of years employment experience the entrepreneur has, *'exp'*, the magnitude of collateral, *'coll'*, the size of the small business in terms of recent sales turnover, *'sales1'* and finally, the entrepreneur's age, *'age'*.

I use a difference of means test to establish differences between the two groups. We can see that interest margins are slightly higher for borrowers with previous borrowing histories and that this difference is significant at the 1 percent level. Rather suprisingly, borrowers with pre-existing relationships tend to borrow less on average than borrowers without these relationships and the significance level for the t-statistic is less than 1 percent. Borrowers without *entrepreneur-bank* relationships tend to have about 9 months more employment experience than borrowers without these relationships and the difference is also significant at the 1 percent level. Regarding collateral, borrowers without *entrepreneur-bank* relationships provide on average less collateral than their counterparts. This difference in the means is significant at the 5 percent level. The remaining two variables, *'sales1'* and *'age'*, show no significant differences in their means.

Table 7.4 reports the corresponding differences between the relative proportions for the dummy variables. These variables are as follows: *'overdrft'*, denotes that a borrower takes out an overdraft (L/C) rather than a fixed term loan, and *'debtres'* indicates that the borrower has needed to have his borrowings rescheduled in the past. The financial distress variable, *'anyinso'*, indicates that the borrower has been insolvent in the past. The variable *'liq1'* indicates that the borrower invests his own savings in the business venture or carries over profits from a previous time period. The dummy *'busoper'* indicates that the entrepreneur has got a partner or key employee who can take over the business in the absence of the business principal. This variable is closely related to the dummy variable *'partner'* indicating that the business was a partnership. It is intuitive that a partnership will experience fewer problems with succession issues than an owner-managed business. Indeed, the correlation between the two variables of 0.135 is significant at the 1 percent level and indicates that partnerships are also businesses with fewer problems regarding succession[12]. The variable *'norisk'* indicates that the entrepreneur stated on his application form, that he did not think that his business project was likely to encounter any risks ahead. The final variable *'working'* denotes whether the loan purpose is designated for working capital purposes.

We can see that there is a structural difference in the breakdown of finance, where firms with *entrepreneur-bank* relationships are more likely to take out an overdraft, *'overdrft'*, than a term loan. The relative proportion for borrowers with a pre-existing relationship stands at 60 percent, compared to 49 percent for through-the-door applicants and this difference is significant at the 1 percent level.

Of businesses with *entrepreneur-bank* relationships, only 1.5 percent have exhibited past insolvency compared with 1.7 percent of their through-the-door counterparts but this disparity is insignificant.

Of borrowers with *entrepreneur-bank* relationships, 9.6 percent have needed their borrowings rescheduled compared with 20.6 percent of through-the-door applicants. This result seems suprising because we would expect the lender to be more lenient to its existing customers than its through-the-door business applicants. However, it may well be the case that a certain amount of debt consolidation is required for ab initio customers and that this is reflected in this high proportion of rescheduled borrowing. However, borrowers who have had their borrowings rescheduled are less likely to obtain an overdraft than other borrowers. This is evidenced by a Spearman's rho of –0.080 for the variable *'debtres'* when it is correlated with overdraft finance *'overdrft'*. This correlation is significant at the 1 percent level. We can conclude from this that the bank might not be as selective about which customers it lends to rather than selective about the financial products that it makes

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[12] Of course it is possible that some partners are sleeping partners who merely inject equity into the business. However, if several partners are actively involved in running the business, there is a higher likelihood that the withdrawal of the principal partner will adversely affect the continuity of the business.

available to them. Therefore, while keen to win new customers, the bank also appears to tailor its financial products to the borrowers' risk profiles.

Of businesses with *entrepreneur-bank* relationships, 70 percent invest their own cash in their business project or have shown a retained profit compared with 76 percent of through-the-door borrowers. This suggests that those entrepreneurs with reputations are less likely to face onerous requirements regarding their financial commitment to their business projects or the past viability (profits) of their projects. Despite the higher demands imposed on through-the-door customers regarding project viability, and their own commitment to the project, we must remember that on average, borrowers with *entrepreneur-bank* relationships post more collateral than their counterparts (From **Table 7.3**). This latter result could be influenced by the cumulative effect of collateral that was previously posted on past personal borrowing. An inexact relationship therefore may exist between the magnitude of the present business loan, *'borr'*, and the level of collateral *'coll'* due to this artefact of the data. Furthermore, due to collateral indivisibilities, collateral is not necessarily priced to risk[13].

Similarly, less onerous requirements are imposed on businesses with *entrepreneur-bank* relationships, regarding the continuity of their business (succession issues). They are significantly less likely to have a key employee or business partner to take over the business operations in the absence of the business principal. The onus is most likely on through-the-door applicants to allocate some individual to fulfil this role in order to make themselves more appealing to a lender. In the same way, through-the-door applicants are significantly more upbeat about the viability of their projects. Of through-the-door applicants, 58 percent stated that their project would not encounter any risks compared with 55 percent of entrepreneurs that had banked with the lender before. The remaining two variables, *'partner'* and *'working'*, did not exhibit any significance in their relative proportions between the two groups.

7.7 Regression results for the factors influencing the price of credit

Now that I have presented the descriptive statistics showing the relative breakdown of the variables according to whether borrowers had established a reputation or were through-the-door applicants, I move on to estimations where I can control for all explanatory variables simultaneously. I regress the interest rate margin *'interest'* against the other explanatory variables and, in so doing, adhere to the same broad variable groups as used by Petersen and

[13] See **Chapter 9** for a comprehensive discussion of collateral

Rajan (1994). These groups comprise the relationship, loan contract, size, borrower/business attributes and finally risk/performance variables (**Table 7.5**).

First, it should be noted that the adjusted r-square value of 0.29 is higher than those reported by Petersen and Rajan (1994) and Berger and Udell (1995). The former reported a maximum adjusted r-squared value of 0.158 while the latter cited a maximum unadjusted value of 0.095. Therefore, my model represents a comparatively good fit to the data with higher levels of explained variance.

Consistent with what we have already seen in the cross-tabs and their corresponding statistics, borrowers exhibiting *entrepreneur-bank* relationships ('*prevbor*'=1) are associated with higher interest margins. The raw coefficient for the *entrepreneur-bank* relationship proxy ('*prevbor*'=1) is 0.161 and this is significant at the 1 percent level. This means that borrowers with previous bank borrowings show an increase in their interest rate margin of 16.1 basis points compared with borrowers who have no previous borrowing experience. I therefore have initial evidence that the sign of the relationship variable coefficient corresponds with theories predicting that borrowers are *'informationally captured'* by the bank (Sharpe, 1990). If banks enjoy the monopoly power conferred by private information as is argued by Sharpe (1990) and Greenbaum et al. (1989), the result should be reflected in higher interest rates in the second round of finance and hence a positive sign for the coefficient on the relationship variable.

I now look at the loan contract variables beginning with the loan type dummy '*overdrft*'. The raw coefficient of 0.418 indicates that borrowers with overdrafts are expected to pay 41.8 basis points more for their borrowings. This relationship is significant at the 1 percent level. It is no suprise that overdraft finance is more expensive than other types of finance. This is because it is flexible (an option to draw down finance at a predetermined, fixed interest rate at some future time-period) and likely to be non-asset backed if used to finance working capital (Berger and Udell, 1995).

Analogous to the higher expected cost of overdraft finance, is the higher expected cost of working capital finance where borrowers taking out a working capital loan are expected to pay 19 basis points more for their finance. The corresponding raw coefficient for the variable '*working=1*' is 0.190. This relationship is again significant at the 1 percent level.

The next variable in the group of loan contract variables is the variable '*borr*'. The interest margin is negatively related to the amount borrowed with a coefficient of $-5.5 * 10^{-6}$. This result is intuitive because the per unit transaction and information monitoring costs of larger loans are lower. An increase in the amount borrowed of £10,000 causes an expected reduction in the interest margin of 0.055 percent which is equivalent to 5.5 basis points. However, the expected reductions with successive increases in borrowing show a tailing-off effect, as seen in the positive value of the coefficient of borrowing squared '*borr2*'. Therefore larger reductions in the interest rate margin are expected at comparatively low levels of borrowing. Successive reductions in interest rate margins with higher levels of borrowing should decrease at a decreasing rate. Eventually, for borrowings above £552,360 the interest margin will increase (at an increasing rate)[14].

I next look at the impact of collateral level *'coll'* on interest margins. Interest rates are decreasing in collateral amount, as one would expect with a trade-off between the two risk instruments. Its non-standardised coefficient of $- 1.371 * 10^{-6}$ indicates that if a borrower increases the amount of collateral borrowed by £100,000, the expected reduction in interest margin is 0.1371 percent, or approximately 14 basis points. However, as with the amount borrowed, the collateral variable, '*coll*', shows a tailing-off effect as evidenced by the positive and significant sign of its squared coefficient.

Leaving the loan contract variables and turning to the size variable, turnover '*sales1*', I note that it is non-significant.

The next category of explanatory variables is that containing the business/borrower attributes. These variables are important because they can be gleaned from the application details of the borrower and can help reduce information asymmetry problems. The variables in this group which have coefficients significant at the 1 percent level are '*dob1yr*', the number of years industrial experience, and '*dob1yr2*' representing experience squared. Also the dummy variable, '*busoper*', indicating whether the continuity of the business is assured in the absence of the owner and *'partner'*, indicating that the entrepreneur has at least one business partner. Finally, the entrepreneur's age, *'age'* is significant and the fact that he retained a profit, *'retain1'*.

An entrepreneur can expect a reduction in his interest margin of 2.1 basis points for each additional year of prior work experience he has. This corresponds to a non-standardised coefficient of -.021 or a reduction of 0.021 percent in the interest margin. As we would expect, this effect tails off because additional work experience is most valuable at a low initial levels of work experience. Therefore the coefficient of experience squared, '*dob1yr2*', has the expected positive sign. Combining the work experience and experience-

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[14] This value of £552,360 is calculated by differentiating interest rate with respect to borrowing (δ int/δ borr) and setting the result of the first derivative equal to zero. When (δ^2int/δ borr^2) > 0 the interest margin by borrowed amount schedule is at the minimum point £503,000 before interest rate rises again

squared variables, an entrepreneur who has 20 years work experience is expected to receive a reduction in his interest rate margin of 40.7 basis points compared with a person with no work experience[15].

The dummy variable *'busoper'* representing the continuity of the business, is the variable from the business attribute group that induces the greatest expected reduction in the interest rate margin. A business whose continuity is assured, is expected to receive a cut of 24.2 basis points (0.242 percent) in its interest rate margin compared to a business where the continuity of the business is not guaranteed.

The only other two variables in the borrower attribute category whose coefficients are significant to at least the 1 percent level is entrepreneur age, *'age'*, and the dummy variable *'partner'*, denoting that there is more than one business owner. An increase of one year in the entrepreneur's age is associated with an expected decrease in the interest margin of 0.017 percent or 1.7 basis points. I checked for a non-linear relationship in the age term but this was non-significant, indicating that the percentage is steadily decreasing with age. Since the relationship between interest rate and age is linear, an increase in age of 40 years, from 18 to 58, should prompt an expected reduction in the interest rate of 68 basis points (40 * 0.017) or 0.68 percent. More mature entrepreneurs are associated with cheaper credit, all things equal.

Finally, the variable *'partner'*, which is complementary to the business continuity variable *'busoper'* described earlier, has a coefficient of -0.04. This indicates that businesses with more than one equity holder or owner (broader ownership structures) are expected to receive cheaper credit than businesses without such structures. The expected difference is 4 basis points. This result of the positive return to the variable *'partner'* is broadly in line with the prediction of Cressy (1996c) who hypothesises that the number of business proprietors is positively associated with what he refers to as *'group'* human capital, and ultimately with survival[16]. I can interpret this *'group'* human capital effect as the benefit to a business of possessing a broader skills and decision-making base than an owner-managed business. The additional benefit enjoyed by a business with several partners has to do with its lower likelihood that it will experience succession issues. However, this effect is already captured by the variable *'busoper'*.

The combined marginal effect of a business with a diffused ownership structure and which is assured continuity on the death of the owner is 4 plus 24.2 basis points (marginal effect of *'busoper'* plus *'partner'*) or 28.2 basis points. This indicates a cut in the interest margin of

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[15] Calculated as $-0.02066 * 20 + 4.21 * 10^{-4} * 20 = -0.4132 + .00842 = -0.4047$

almost a third of a percent. It therefore follows that the lender conditions its interest rates, to some extent, on the long-term prospects of the business. In other words, the bank reacts more positively to businesses which, if they survive, can evolve into enterprises whose prospects are not dependent on the health, ability or financial affairs of the main owner. Edwards and Fisher (1994) have noted continuity issues as being important to decisions made by German banks when lending to small businesses. The benefit the guarantee of business continuity confers to the business is seen in the negative sign on the coefficient of '*busoper*'.

A firm that has retained a profit, '*retain1*'=1, is associated with a higher interest margin, all things equal. This effect is approximately 5 basis points or 0.049 percent. My explanation for this is that perhaps such firms are in a better position to pay a marginally higher interest margin than others. However, a possible counter-argument would be that such firms should have better negotiating power with a lender over their interest margin.

The remaining variable in the borrower/business attribute category, '*norisk*', is non-significant.

Finally, I come to the performance/risk category. Both variables, namely whether the owner was insolvent in the past, '*anyinso*', and whether the loan was rescheduled, '*debtres*', are significant. Interest margins are unexpectedly negatively related to the risk dummy '*debtres*'. This is contrary to what I would expect but it may reflect the lender converting a troublesome overdraft to a term loan on a lower interest schedule. However, consistent with what I would expect and with the findings of Petersen and Rajan (1994), past insolvency, '*anyinso*', is associated with higher interest rate margins. If an entrepreneur has been insolvent in the past, the interest margin he is expected to pay is 30.2 basis points (0.302 percent) higher than an entrepreneur who has never gone bankrupt. Lending to past bankrupts must be regarded as high risk and carry a higher default premium. This is consistent with the lender adopting a risk based pricing policy.

I now examine the incremental value of the variable groups in order to establish how much of the explanatory power of the model is due to each group in turn (**Table 7.6**).

Starting with the relationship dummy '*prevbor*', we see that the adjusted r-square is only 0.013 when it is entered as the single explanatory variable. It is only when I add the contract variables that the adjusted r-square rises to 0.27, which is close to its value in the full model of 0.29. The marginal contribution of the loan contract group in terms of the increase in the sum of squares explained by the model (explained variance) is 1,924 (i.e. 2,019 minus 95). I

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[16] Cressy (1996). P.1,258

derive this value by subtracting the model sum of squares when loan contract variables are excluded from the model sum of squares when loan contract variables are included. This value of 1,924 is the highest achieved on the addition of any individual group to the model. Therefore, the loan contract group is the most important in explaining the interest margin.

It is interesting that neither Petersen and Rajan (1994) nor Berger and Udell (1995) included amount borrowed '*borr*' nor collateral value '*coll*' in their loan contract variable groups[17]. I argue that including borrowed amount is advisable due to the high explanatory power of its coefficient. Apart from its explanatory power, there are sound a priori arguments for including borrowed amount in the estimations. The reduction in the transaction costs of borrowing per pound borrowed when the amount borrowed increases, should prompt future research to consider amount borrowed as a useful explanatory variable for the cost of credit.

The next group of variables whose contribution to the model is considered is the business/borrower attribute category. This group has a marginal contribution to the sum of squares for the model of 168 i.e. 2,187 - 2,019. The r-square value increases from 0.27 to 0.29. The final group to be added to the model is the group containing the performance/risk variables. The adjusted value for the r-squared remains the same at 0.29. The increase in the model sum of squares is a mere 13 (2,285 – 2,274).

It can be concluded that the loan contract variable group is the most important in explaining interest margins.

There was a final issue that I had to investigate before concluding this empirical section. It is possible that the collateral variable, *'coll'*, is partially determined by the amount borrowed, *'borr'*[18]. This is not an endogeneity problem (rather a collinearity issue) because the response variable, *'interest'*, should not determine the level of collateral nor the amount borrowed and hence the causality is in the direction described by my model in **section 7.5**. The reason my model predicts the interest margin based inter alia on the level of collateral and loan amount is intuitive. A small business owner comes to the bank and fills in his application details. He requests a certain level of funding ('*borr*') and is asked to post a certain portion of his assets as collateral. Only when the bank has considered all these application details and the term and structure of the funding is an interest margin set. Therefore, the setting of the interest margin occurs ex post the decision to grant a specific amount of finance for a specific level of collateral. Although it is possible that the interest

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[17] Petersen and Rajan (1994) and Berger and Udell (1995) use collateral dummies indicating whether collateral was taken or not on loans. Their omission of collateral *amount* may be due to an artefact of the data rather than an oversight on their part

margin could influence the level of collateral if the borrower negotiated the transfer of more collateral as a quid pro quo for receiving a lower interest rate, the likelihood of this happening is low. I argue that negotiation based on collateral is unlikely because first-time business borrowers are likely to post *all their assets as collateral*. Entrepreneurs post all their appropriate assets as collateral because initial wealth is low, the bank does not accept any collateral other than land, buildings (likely to be the entrepreneur's house) and life assurance policies. Hence there is little latitude for negotiating more favourable interest margins based on the posting of additional collateral. Moreover, in a separate analysis using similar data, Burke and Hanley (2002) found that collateral to loan amount ratios were relatively invariant for first-time business borrowers suggesting that additional collateral is not posted in order to secure lower interest margins. A final reason for including collateral as an explanatory variable is based on the existing studies into the price of borrowing by Petersen and Rajan (1994) and Berger and Udell (1995) where collateral is used as an explanatory variable.

Table 7.7 demonstrates what happens the regression explaining the price of credit when either collateral, loan amount or both collateral and loan amount are excluded from the estimations. Column (1) shows the full model with both variables included. In Column (2) the borrowing variables, *'borr'* and *'borr2'* are excluded. The significance levels of none of the other variables change although the values of the coefficients of the collateral variables, *'coll'* and *'coll2'* change. This change in the values of the coefficients reflects the collinearity of the collateral level variables with the borrowing level variables. The coefficient of the variable *'coll'* falls from –0.154 to –0.356. The r-square value drops from 0.293 to 0.242 indicating a worse fit for the model in the absence of the borrowing level variables. When in column (3), the collateral level variables are excluded from the estimation but the borrowing level variables are retained, the significance levels of the other explanatory variables remain the same but the coefficients of the borrowing level variables increase, again denoting collinearity. Finally, if both the collateral and borrowing level variables are dropped from the estimation as seen in column (4), the r-squared value for the model drops from 0.293 to 0.195. Variables most affected by the exclusion of the collateral and borrowing level variables on the basis of changes to their coefficients are *'working'*, *'overdrft'*, *'sales1'*, *'partner'* and *'age'*. It is worth highlighting that the most significantly affected variable is the size proxy, *'sales1'* which becomes significant for the first time. This

[18] Indeed, in my analysis in **Chapter 9**, I investigate the issues determining the level of collateral and find that collateral is conditioned on the amount borrowed and the structure of the loan.

suggests that the levels of borrowing and collateral already indicate the relative size of a small business and render the size proxy redundant until they are excluded.

7.8 Conclusion

There are several implications of my analysis for the cost of credit for small, young firms. Firstly, firms with existing *entrepreneur-bank* relationships prior to their application for a loan, pay on average 16 basis points more for their borrowing than through-the-door business applicants. This result may appear counter-intuitive but it agrees with models by Sharpe (1990) and by Greenbaum et al. (1989) that banks offer first-term borrowers lower interest rates than second-period borrowers[19].

However, previous theoretical and empirical studies have not adequately considered the role of the changing structure of finance over the business growth cycle in the context of interest margins. As a business evolves from a start-up to an established business, its demand for finance may change according to its need for increased/decreased working capital finance, vis. a viz. asset backed finance. My analyses show that the financial structure differs between first and second-period borrowers, where second-period borrowers are more likely the receive overdraft finance. However, even when I consider the different structure of finance by loan type and purpose, second-period borrowers are still charged comparatively more for their finance than first-period borrowers[20].

The reason that second-period borrowers incur higher costs for their finance than through-the-door applicants could well be due to prohibitively high exit costs as modelled by Greenbaum et al. (1989). Alternatively, my results may be explained by Sharpe's (1990) theory that businesses are *'informationally captured'*. He argues that even though banks earn zero profits over the life cycle of the average customer relationship, that they are not disciplined by the market to offer better-performing customers 'competitive' rates.

'Due to competition....rents are competed away via lower interest rates offered to all firms in their initial period, precisely when banks know least about firms'[21].

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[19] Since the degree of market concentration plays a central role in the theoretical model by Petersen and Rajan (1995), it is unfortunate that I could not easily test for this because my data was obtained from one bank. I suspect however, that the UK credit market for business loans is concentrated judging by concerns raised recently by the Bank of England concerning the competitiveness of UK banks in the small business sector. Bank of England (2001): Financing of Technology-Based Small Firms

[20] Unfortunately, my data did not contain arrangement fees for overdrafts. If it had, it is likely that the relative cost differential between first- and second period borrowers would have increased even further since second-period borrowers are more likely to receive overdraft finance.

[21] P. 1,070. Sharpe (1990)

What is certain, is that second-period borrowers pay more for their finance, even when finance type and purpose are controlled for, and are more likely to take out higher risk, more expensive overdraft finance. Entrepreneurs who take out an overdraft in-lieu of a loan are expected to pay 42 basis points more for their borrowing.

There is scope for future research to tease out a possible relationship between the evolution of a firm's demand for finance over time as well as the transition from loan to overdraft finance. Given the difficulties that start-up firms experience with overtrading and financing their working capital, it seems anomalous that they would prefer loans to overdrafts. An overdraft is better tailored towards working capital requirements. For this reason, the fact that 'through-the-door' applicants are less likely than firms with *entrepreneur-bank* relationships to receive overdraft finance may have more to do with supply than demand issues.

An additional outcome of my analysis is that collateral and interest rates are substitutable. An increase of £100,000 in the value of collateral, reduces the interest margin by 0.137 percent or approximately 14 basis points. This suggests that firms that have comparatively higher asset levels may be able to trade off higher collateral levels against a reduction in interest margins.

Similarly the entrepreneur can expect a reduction of 5.5 basis points on his interest margin for a £10,000 increase in the amount borrowed. My finding that interest margins are decreasing in the amount borrowed, underpins the conjecture of Petersen and Rajan (1994) that there may be some price embeddedness in the volume of borrowing meaning that loans are transaction-driven.

However, the bank is not motivated entirely by transaction based lending, as seen in importance of the business attribute variables especially those dealing with ownership dispersion and employment experience. If interest margins showed 'embeddedness' as Petersen and Rajan (1994) suggest, the bank would respond only to the magnitude of the loan or overdraft when setting the interest margin. Hence with 'embeddedness', the margin charged for borrowing would reflect the transaction cost of making that loan. However, we have seen that the bank does respond the human capital characteristics of the borrower when pricing loans and overdrafts. We see this responsiveness of the bank to borrower attributes where it charges mature, more experienced entrepreneurs less on their borrowings than younger and less experienced entrepreneurs. The bank also rewards businesses which can continue to operate in the absence of the business owner and which have a shared ownership structure by charging such businesses less on their borrowings.

In answer to my research question of whether the bank is more transaction driven or human capital oriented, I conclude that the bank bases the price of credit more on transaction variables rather than on human capital variables. This is evidenced by the higher explanatory power of the loan contract variables as a group. The marginal contribution of the loan contract group in terms of the increase in the sum of squares explained by the model (explained variance) is 1,924. This is the highest marginal contribution of any of the groups added to the model. Although my list of human capital variables is not exhaustive, I have initial evidence that transaction-cost variables such as borrowing purpose, the amount borrowed and the type of loan facility used, are key factors considered by the lender when setting the price of a loan.

The cheaper cost of first-term finance is good news, at least for start-ups and businesses without a track record, but not for borrowers in subsequent periods. This supports the argument for implicit contracts of the type described by Sharpe (1990) in order that businesses developing reputations and surviving into the second period will be rewarded rather than penalised for their efforts. Moreover, it suggests that first-term loans are subsidised by the bank. However, this subsidisation does not continue into second-period finance. Subsidisation exists even when potential distortions, which impact on the cost of finance, are taken into account. Controlling for these other factors (whether the finance is an overdraft or not, the amount borrowed and the amount of collateral given), does not overturn my conclusion that first-term finance is cheaper than finance in subsequent periods. I conclude that *entrepreneur-bank* relationships influence interest margins, whereby they increase rather than decrease the price of credit.

Table 7.1 List of variable names

Variable names	Description
age	Continuous variable denoting the age of the entrepreneur
age2	Entrepreneur's age squared
anyinso	Borrower has been insolvent or bankrupt in the past(*anyinso*=1 if bankruptcy occurred)
borr	My measure for new borrowing requested Sum of loan, overdraft and other amount requested (overlap with agg_borr)
borr2	Borrowing squared
busoper	The business can continue to exist without the founder. Measure of dispersion of ownership (busoper=1 if 'Yes')
coll	Sum of owner's equity injected into the project in addition to the liquidation value of land, buildings and life policies offered as collateral
debtres	Borrower has had to have his loan rescheduled on a different timeframe. Denotes financial distress and difficulty meeting repayments. (debtres=1 if 'Yes')
doblyr	Experience of borrower in current industrial sector
doblyr2	Experience in industrial sector squared
interest	Interest rate margin (margin above the base rate)
nonborr1	Entrepreneur has injected own cash savings into the business project
norisk	Borrower believes that he will have no business or financial risks in the year ahead. Denotes borrower confidence (norisk=1 if 'Yes')
overdrft	Loan purpose is overdraft (overdrft=1) rather than loan (overdrft=0)
partner	Main owner has a business partner
prevbor=1	Previous cumulative aggregate borrowing (dummy variable=1 if applicant has previous borrowing)
retain1	Business has retained a profit
sales1	Current or projected sales (size proxy)
working	Borrowing used to finance working capital as opposed to any other type of asset backed loan

Table 7.2 Private information models

model	information	bank concentration	prediction for first-period finance
Petersen and Rajan (1995)	Non-observable	either high or low	rate in concentrated market period 2 > rate in competitive market period 1
			rate in concentrated market period 1 < rate in competitive market period 1
Boot and Thakor (1994)	Non-observable	low	interest rates period 1 > interest rates period 2
Greenbaum et al. (1989)	Non-observable	low	interest rates period 1 < interest rates period 2
Sharpe (1990)	Non-observable	low	interest rates period 1 < interest rates period 2
Diamond (1989)	Observable to other lenders	Not-specified	interest rates period 1 > interest rates period 2

Table 7.3 Breakdown in continuous variables according to whether applicant has *entrepreneur-bank* relationship or not

	Mean for businesses with *entrepreneur-bank* relationships	Mean for 'through-the-door' businesses	t	Sig. (Equal variances not assumed)
interest	3.49	3.17	-8.19	0.00
borr	52,225	73,938	6.75	0.00
exp	11.9	12.7	2.63	0.01
coll	65,773	54,970	-2.10	0.04
sales1	531,999	240,710	-0.84	0.40
age	43.5	43.4	-0.24	0.81
Total number	1,152	4,816		

Table 7.4 Breakdown in proportions for binary variables according to whether applicant has *entrepreneur-bank* relationship or not

	Of businesses with *entrepreneur-bank* relationships, % with attribute	Of 'through-the-door' businesses, % with attribute	Cramer's V	Significance Cramer's V
overdrft	60	49	0.0904	0.0000
anyinso	1.5	1.7	-0.006	0.621
debtres	9.6	20.6	-0.112	0.0000
liq1	70	76	0.0556	0.0000
busoper	72	78	0.0584	0.0000
norisk	55	58	0.0270	0.0369
partner	53	52	0.0117	0.3667
working	53	53	0.0049	0.7049
Total number	1,152	4,816		

Table 7.5 Influence of *entrepreneur-bank* relationships on interest margins

Dependent variable = interest margin ('interest')				
	Unstd. est.	t stat	P> t	Std. est.
Explanatory Variables				
Intercept	4.162	23.146	0.000	
Relationship				
Previous borrowing ('prevbor'=1)	0.161***	5.113	0.000	0.057***
Loan contract				
Working capital ('working'=1)	0.190***	6.242	0.000	0.085***
Borrowed amount ('borr')	-5.5214-6***	-19.889	0.000	-0.497***
Borrowed amount squared ('borr2')	4.998E-12***	13.263	0.000	0.303***
Collateral level (*'coll'*)	-1.371E-6***	-6.910	0.000	-0.154***
Collateral level squared (*'coll2'*)	9.309E-13***	4.764		0.098***
Overdraft finance ('overdrft'=1)	0.418***	13.564	0.000	0.187***
Entrepreneur has injected own equity into project ('nonborr1'=1)	-6.671E-2***	-2.423	0.015	-0.029**
Size				
Recent or projected sales income ('sales1')	-1.699E-9	-0.727	0.468	-0.008
Borrower/business attributes				
Principal has business partner ('partner'=1)	-4.188E-2*	-1.685	0.092	-0.019*
Age of entrepreneur ('age')	-1.745E-2**	-2.149	0.032	-0.158**
Age of entrepreneur squared ('age2')	1.073E-4	1.207	0.227	0.089
Yrs. employment experience in similar business ('dob1yr')	-2.066E-2***	-5.909	0.000	-0.174***
Yrs. employment experience squared ('dob1yr2')	4.214E-4***	4.558	0.000	0.135***
Continuity of businesses death of owner ('busoper'=1)	-0.242***	-7.931	0.000	-0.091***
Business owner optimistic ('norisk'=1)	-3.360E-2	-1.333	0.183	-0.015
Entrepreneur has retained a profit ('retain1'=1)	4.940E-2*	1.886	0.059	0.021*
Performance/risk				
Finance has been rescheduled ('debtres'=1)	-7.005E-2**	-2.078	0.038	-0.024**
Past insolvency ('anyinso'=1)	0.302***	3.152	0.002	0.034***
Number of observations	5,968			
R-square	0.293			
Adj. R-square	0.290			
* sig. at 10 percent level				
** sig. at 5 percent level				
*** sig. at 1 percent level				

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Table 7.6 Contribution of explanatory variable groups predicting interest margins

Dependent variable = interest margin ('interest')	Standardised estimates			
	Relationship	Loan contract	Borrower attributes	Performance /risk
Previous borrowing ('prevbor'=1)	0.113***	0.062***	0.059***	0.057***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Working capital ('working'=1)		0.067***	0.085***	0.085***
		(0.000)	*(0.000)*	*(0.000)*
Borrowed amount ('borr')		-0.531***	-.501***	-0.497***
		(0.000)	*(0.000)*	*(0.000)*
Borrowed amount squared ('borr2')		0.325***	0.305***	0.303***
		(0.000)	*(0.000)*	*(0.000)*
Collateral level ('*coll*')		-.189***	-0.160***	-0.154***
		(0.000)	*(0.000)*	*(0.000)*
Collateral level squared ('*coll2*')		0.123***	0.103***	0.098***
		(0.000)	*(0.000)*	*(0.000)*
Overdraft finance ('overdrft'=1)		0.200***	0.189***	0.187***
		(0.000)	*(0.000)*	*(0.000)*
Entrepreneur injects own equity ('nonborr1'=1)		-0.025**	-0.023**	-0.029**
		(0.034)	*(0.043)*	*(0.015)*
Business size proxied by current or projected sales ('sales1')			-0.008	-0.008
			(0.479)	*(0.468)*
Business has retained a profit or savings ('retain1'=1)			0.019*	0.021*
			(0.086)	*(0.059)*
Has business partner ('partner'=1)			-0.019*	-0.019*
			(0.081)	*(0.092)*
Age of entrepreneur ('age')			-0.160**	-0.158**
			(0.030)	*(0.032)*
Age of entrepreneur squared ('age2')			0.089	0.089
			(0.229)	*(0.227)*
Yrs. employment experience in similar business ('dob1yr')			-0.176***	-0.174***
			(0.000)	*(0.000)*
Yrs. employment experience squared ('dob1yr2')			0.138***	0.135***
			(0.000)	*(0.000)*
Continuity of business on death of owner ('busoper'=1)			-0.092***	-0.091***
			(0.000)	*(0.000)*
Business owner optimistic ('norisk'=1)			-0.017	-0.015
			(0.133)	*(0.183)*
Finance has been rescheduled ('debtres'=1)				-0.024**
				(0.038)
Past insolvency ('anyinso'=1)				0.034***
				(0.002)
Adj. R-square	0.013	0.270	0.292	0.293
F value	77.353	276.872	145.472	131.196
Sum of squares (model)	95.377	2,019.202	2,187.786	2,200.582
Number of observations	5,967	5,967	5,967	5,967

Table 7.7 Check for independent contribution of collateral and amount borrowed

Dependent variable = interest margin ('interest')	Standardised estimates			
	(1)	(2)	(3)	(4)
Previous borrowing ('prevbor'=1)	0.057***	0.080***	0.052***	0.073***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Working capital ('working'=1)	0.085***	0.109***	0.087***	0.130***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Borrowed amount ('borr')	-0.497***		-0.57***	
	(0.000)		*(0.000)*	
Borrowed amount squared ('borr2')	0.303***		0.334***	
	(0.000)		*(0.000)*	
Collateral level ('*coll*')	-0.154***	-0.356***		
	(0.000)	*(0.000)*		
Collateral level squared ('*coll2*')	0.098***	0.193***		
	(0.000)	*(0.000)*		
Overdraft finance ('overdrft'=1)	0.187***	0.247***	0.179***	0.255***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Entrepreneur injects own equity ('nonborr1'=1)	-0.029**	-0.034***	-0.031***	-0.039***
	(0.015)	*(0.009)*	*(0.009)*	*(0.002)*
Business size proxied by current or projected sales ('sales1')	-0.008	-0.010	-0.011	-0.019*
	(0.468)	*(0.329)*	*(0.329)*	*(0.10)*
Business has retained a profit or savings ('retain1'=1)	0.021*	0.015*	0.022*	0.016
	(0.059)	*(0.054)*	*(0.054)*	*(0.189)*
Has business partner ('partner'=1)	-0.019*	-0.028*	-0.020*	-0.035***
	(0.092)	*(0.069)*	*(0.069)*	*(0.003)*
Age of entrepreneur ('age')	-0.158**	0.227**	-0.165**	-0.291***
	(0.032)	*(0.026)*	*(0.026)*	*(0.000)*
Age of entrepreneur squared ('age2')	0.089	0.155	0.090	0.197***
	(0.227)	*(0.226)*	*(0.226)*	*(0.012)*
Yrs. employment experience in similar business ('dob1yr')	-0.174***	-0.175***	-0.18***	-0.191***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Yrs. employment experience squared ('dob1yr2')	0.135***	0.26***	0.141***	0.137***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Continuity of business on death of owner ('busoper'=1)	-0.091***	-0.107***	-0.093***	-0.123***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Business owner optimistic ('norisk'=1)	-0.015	-0.001	-0.016	0.002
	(0.183)	*(0.908)*	*(0.159)*	*(0.883)*
Finance has been rescheduled ('debtres'=1)	-0.024**	-0.045***	-0.032***	-0.076***
	(0.038)	*(0.000)*	*(0.007)*	*(0.000)*
Past insolvency ('anyinso'=1)	0.034***	0.032***	0.036***	0.035***
	(0.002)	*(0.004)*	*(0.001)*	*(0.003)*
Adj. R-square	0.293	0.242	0.287	0.195
F value	131.196	113.282	142.603	97.579
Sum of squares (model)	2,200.582	1822.041	2157.129	1470.755
Number of observations	5,967	5,967	5,967	5,967

Chapter 8

The reason why a bank rejects a small business loan

8.1 Introduction and contribution of this chapter to the literature

This chapter deals with the decision to lend or otherwise to a new small business borrower. Since small businesses are primarily reliant on banks for their access to finance, the availability of credit has always been to the forefront of research into small business finance (Hancock and Wilcox, 1998; Cressy, 1996; De Meza and Southey, 1996; Evans and Jovanovic, 1989).

Notwithstanding the importance attached to this research area internationally, the lack of data relating to the bank rejection decision has hampered empirical work in this area. There is only one empirical analysis investigating the bank sanctioning decision for commercial borrowers and this relates to the US only (Cole, 1998) [1]. Cole applies the NSSBF (National Survey of Small Business Finances) survey data to his analysis of what factors prompt a bank to reject a commercial loan. He emphasises the role of business-bank relationships and concludes that a potential lender is more likely to grant finance to a commercial borrower with whom it has a pre-existing relationship.

However, the analysis by Cole omits potentially important variables relating to the characteristics of the entrepreneur and of his business.

The aim of this chapter is twofold. I set out to use unique and thitherto unused data relating to 5,968 UK commercial borrowers to address the question of which factors motivate a bank to reject a funding application to a new commercial borrower. The data refers to applications within the period 1998 to 1999 and which are relatively homogeneous, where all applicants are first-time commercial borrowers and therefore without a business track record at the bank. 1,152 of the 5,968 borrowers have pre-existing non-commercial borrowing relationships with the bank compared with 4,816 through-the-door applicants. Because all applicants in our data are applying for their first commercial loan with the lender, our data permits us to estimate the importance of *non-commercial* borrower relationships in a way that has not been possible before. This constraint allows me infer the value of entrepreneur-bank relationships when a commercial borrower does not have a business track-record with the bank but does not rule out the possibility that the bank has access to in-house information on any non-commercial accounts relating to the applicants.

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[1] Leonard (1992) also uses a sample of accepted and rejected commercial for 283 loan applications but this is not an analysis that looks at the sanctioning decision. It is primarily concerned with scoring issues and achieving a separation between accepted and rejected applicants based on regression techniques.

If information about a commercial applicant is costless, as Diamond (1989) assumes, then the value of pre-existing non-commercial accounts should be zero. However, this is a heroic assumption to make given the cost (and possibly lack in depth) of credit bureau data. Hence, if the market for information is not fully efficient and costless, there will be a value placed on the information conveyed by non-commercial accounts.

I also investigate the degree to which a bank is cautious or risk adverse by measuring the marginal effect of business exposure (collateral and loan amounts) on the sanctioner's decision. If a bank responds positively to increases in collateral provision or increases in the amount of finance requested, then it is concerned about the level of its exposure to a small business. Indeed, previous studies on the effects of collateral have hypothesised the positive effects of collateral usage where collateral can increase an entrepreneur's commitment to a business project, reduce moral hazard and reduce the bank's exposure to the risk of default (Wette, 1983; Bester, 1985; Besanko and Thakor, 1987)[2]. Indeed, Basu and Parker (2001) note that all UK start-ups in their sample who were refused bank funding claimed that this refusal was prompted by their lack of sufficient collateral.

A further feature of this study is that, for the first time, variables are included that describe the quality of an entrepreneur in terms of his age, work experience and his assessment of the risk of this business project[3]. This is deemed particularly important as Mester (1997) points out that of the five separate commercial scorecards introduced in the US by the Fair Isaac plc. Credit rating agency the 'most important indicators of small-business loan performance were characteristics of the business owner rather than the business itself'[4]. This is likely due to the fact that the owners' finances and those of the business are commingled.

I also include variables that relate to the quality of the business itself in terms of its continuity in the absence of the applicant for the business loan, its growth and its liquidity.

By including variables relating to the quality of an entrepreneur, I acknowledge the work of Cressy (1996) who emphasised the importance of borrower characteristics in influencing survival. My hypothesis is that if the survival of businesses is conditioned on characteristics

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[2] Furthermore, some two-period models of bank lending that assume non-costless borrower information, indicate that a bank may reduce its exposure to a risky business in a systematic way by staggering finance over two borrowing periods. In practice, this would lead to introductory lending where a bank would agree to lending a small loan (low overdraft limit) with the possibility of a larger loan (higher limit) in successive applications for finance if the borrower is creditworthy (Jaffee and Russell, 1976; Petersen and Rajan, 1995). Multi-period models assuming costless information such as Diamond (1989) do not conclude that finance is staggered in this way.

[3] The age of an entrepreneur at the time of business start-up was found by Basu and Parker (2001) to be positively correlated with the ability of an entrepreneur to obtain funding from his family. However, other factors may obtain in the ability of an entrepreneur to secure funding from his bank.

[4] P.3, Mester (1997)

of the borrower, then it follows that these characteristics should also influence the bank's decision to accept or reject a business loan[5].

The main finding of this analysis is that the pre-existence of a non-commercial borrowing relationship is by far the most important factor leading to a favourable credit application outcome. I also find that, consistent with what we would expect, borrowers with sullied credit histories are more likely to have their credit applications turned down. Loan sanctioners place importance on the self-financing capability of the firm but borrower attributes such as age and number of years work experience have little or no effect on the sanctioner's decision. This result on the negligible role played by age and work experience when an entrepreneur applies for *bank funding* contrasts strongly with the important contribution of age and work experience variables that was documented by Basu and Parker (2001) when the entrepreneur secures *family funding* for his start-up. It follows that a loan sanctioner's decision is informed more by the past performance of an enterprise or of the business owner than by characteristics of the business principal or of his business.

This chapter is structured as follows. The first section presents the relevant literature on variables affecting the bank's lending decision. In the section following this, I describe my data. I then present some descriptive statistics before supplying the results of the estimations. I conclude in the final section and discuss the implications of my results for first time business borrowers. Finally, my *'E-T'* model that attempts to rationalise some of the results obtained in my estimations in a theoretical framework is contained in the Appendix to this chapter.

8.2 Background

Since first-period business borrowers are primarily reliant on banks for their access to finance, the availability of credit has always been to the forefront of research into small business finance (Hancock and Wilcox, 1998; Cressy, 1996a; Cressy, 1996b; Cressy, 1996c; De Meza and Southey, 1996; Evans and Jovanovic, 1989; Binks and Ennew, 1996). Despite the importance attached to this research area internationally, the lack of data relating to the bank rejection decision has hampered empirical work in this area. There are only two empirical analyses that relate to the bank rejection decision for small businesses (Cole,

[5] Unlike Kon and Storey (2000), we do not explore the implications of bank rejection on the borrower's willingness to apply for funding. It is quite plausible that so-called *'discouraged borrowers'* have not applied to the bank because they anticipate that they will be rejected, hence underestimating the true proportion of borrowers in the population of applicants who are rejected.

1998; Leonard, 1992). However, the analysis by Cole focuses on relationship variables and includes neither human capital variables nor loan contract variables. The analysis by Leonard focuses on prediction rather than explanation and therefore does not explain how the human capital variables included in this analysis relate to the accept/reject decision other than reporting that they are significant.

In this analysis, I follow the lead set by Cole (1998), which is the only existing analysis of this type investigating the factors that influence a sanctioner to reject a small business loan. However, I also include human capital variables and control for the magnitude of the loan and collateral. My analysis therefore represents the first UK analysis of this kind. It is also the first analysis to be able to investigate the dual role of the factors borrowing level and collateral in influencing the accept/reject decision.

The aim of this chapter is twofold. Firstly, I set out to replicate the empirical analysis performed by Cole (1998) but including human capital variables such as the entrepreneur's age and work experience. In so doing, I acknowledge the work of Cressy (1996c) who emphasised the importance of borrower characteristics in influencing survival. My hypothesis is that if the survival of business start-ups is conditioned on human capital variables, human capital variables should also influence the bank's decision to accept or reject a business loan. I argue that it is not enough to include borrower credit history or relationship as the only factors explaining why a bank grants finance to a first-period borrower but that human capital variables should also be included as potential factors influencing the accept/reject decision.

In addition to controlling for human capital variables in my analysis I also, for the first time in an analysis of this kind, control for the value of collateral provided by the small business and the magnitude of the finance requested. The level of collateral is hypothesised to reduce the risk posed by a business applicant and also hypothesised to increase the applicant's commitment to the business project (Wette, 1983; Bester, 1985; Besanko and Thakor, 1987a; Besanko and Thakor, 1987b). If first-period borrowing is put in a multi-period context, the bank will also want to reduce its exposure to the applicant until his credit status becomes known and the business-bank relationship matures (Jaffee and Russell, 1976; Petersen and Rajan, 1995). A bank can opt to stagger finance over two periods where the borrower receives the larger tranche of finance in the second period once the bank is assured of his creditworthiness[6]. During the trial lending period, the bank gathers behavioural

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[6] This view that the amount loaned is a choice variable is challenged by Stiglitz and Weiss (1981) who argue that under investment by banks increases portfolio risk because under capitalised firms are more financially frail

information about the borrower. This situation is in some ways analogous to the strategy employed by some US filling stations where customers are permitted to purchase a dollar's worth of fuel on credit while the customer's credit ratings are checked.

If the bank shows a tendency towards staggered finance, the effect should be an inverse relationship between the likelihood of receiving credit and the amount of credit requested. Therefore, it is necessary to control for the magnitude of the loan and collateral provided as these affect the risk profile of the loan and are hypothesised to affect the accept/reject decision accordingly.

8.3 The literature on credit constraints

I describe what is meant by credit rationing in **Chapter 2, section 2.3**. In this section, I will provide a critique of the models presented in **Chapter 2, section 2.4** (dealing with the availability of credit) because they relate to the bank's decision to accept or decline a small business loan application.

All the theoretical literature points to the existence of asymmetric information where the entrepreneur knows more about his creditworthiness or the viability of his project than the bank (Jaffee and Russell, 1976; Besanko and Thakor, 1987a; Besanko and Thakor, 1987b; Bester, 1985; Stiglitz and Weiss, 1981). The exception to the assumption that the entrepreneur knows more about his credit status than the bank, is in the newer papers where entrepreneurs are deemed naïve, overconfident or simply lacking the overview and experience of a banker (Manove and Padilla, 1999; de Meza and Southey, 1996). The theoretical literature on credit constraints focuses, therefore, on information.

Any empirical analysis on credit constraints has to consider the fundamental question of banker/entrepreneur knowledge or information. In other words, it should ask two questions. The first question is, '*How little does the bank know*?' and the second question is '*How much emphasis is placed on the contract variables (collateral, amount loaned, likelihood of being denied credit and interest margins) as a result of how little the bank knows*?'.

The transitional credit rationing (TCR) model by Jaffee and Russell (1976) describes how the bank minimises its exposure to a first-term borrower in the first lending period while waiting from his creditworthiness to be revealed in the second period. They describe all borrowers as being either honest or dishonest. The decision to be dishonest is influenced by the incentive to default on a loan based on the size of the loan remaining to be repaid compared with the cost of defaulting on that loan. The decision to be honest, on the other hand, is not motivated by the size of the loan.

Default increases the borrower's utility if the cost of default is less than the cost of repaying the loan. The tendency to default for dishonest borrowers is increasing in the size of the loan because the dishonest borrower benefits more (utility increases more) by defaulting on a comparatively large loan when he pockets the outstanding borrowings.

In a pooling equilibrium, where the borrower types cannot be separated out, honest borrowers prefer a loan that is less than the one they requested in return for a lower interest margin (cost of servicing the loan) and some future payoff. Under a future payoff the bank makes good the financial shortfall experienced by the honest borrower in the loan run. Accordingly, the bank will make smaller loans than requested to all borrowers and by doing so will reduce the incentive for dishonest borrowers to default. Under perfect competition, the bank passes on the gains arising from decreased default over its total portfolio to the honest borrowers when their status is revealed over time.

The equilibrium credit rationing (ECR) model by Stiglitz and Weiss (1981) disagrees with the predictions of the Jaffee and Russell model outlined above by observing that reducing the amount loaned to each borrower will not decrease but rather increase level of bank portfolio risk. If a bank lends a lower amount than a business requires for its project, the likelihood of this undercapitalised project succeeding is lower. Therefore the bank's portfolio is riskier because the probability that individual businesses default is higher.

Rather than cutting down the amount loaned to each borrower, the Stiglitz and Weiss model proposes that a better way of dealing with risk than limiting the amount granted to each borrower, is to retain a threshold interest margin below the equilibrium interest margin. At this threshold interest margin, the bank's profits are maximised where the bank allocates loans to a portion of the applicants such that the total amount loaned corresponds to the amount the bank is prepared to supply at the threshold interest margin. Since the demand for loans outstrips the supply of loans at interest margins below the equilibrium interest margin, credit is rationed. The credit rationing implemented by the bank at this threshold interest margin is justified by a demonstration of what would happen if the interest margin were raised above the threshold rate. At interest margins above the threshold interest margin, the marginal gains from the increased interest margin that would accrue to the bank would be negated by the higher default losses arising when higher risk borrowers entered the borrower pool. Higher interest margins would attract more volatile borrower types who would have the same average returns as safer, more stable borrowers but who would have a wider dispersion of project returns around the average return.

Unlike any of the other models, Bester's (1985) model does not predict credit rationing because he argues that the bank can perfectly distinguish high from low risk borrowers through their self-selection of credit contracts comprising a trade-off between collateral and interest margin. The bank will have been so successful in tailoring the terms of the loans that even if a high risk borrower is rejected for a high risk loan, he is unwilling to accept the loan terms offered to his low risk counterpart.

The main cornerstone of the Bester paper is that a set of contracts can be devised such that high and low risk borrowers will prefer one of the risk instruments (interest margins or collateral) to the other. In other words, the marginal rate of substitution or slope of the line showing the trade-off between collateral and interest margins will be unique to each of the borrower groups. Accordingly, Bester's model does not predict credit rationing because he assumes that perfect separation of the risk types can be achieved.

Unlike Bester, Besanko and Thakor (1987b) do not deduce from their credit-rationing model that banks can perfectly separate high from low risk applicants by deriving incentive compatible contracts. Screening is not 100 percent efficient. Their model indicates that with wealth constraints low risk borrowers will have their loans allocated on a lottery basis. In other words, there is non-discriminative credit rationing on loans to low risk borrowers. Credit rationing is used as a deterrent to borrowers wishing to apply for finance.

In the Besanko and Thakor model, what makes a borrower high risk, is his lower probability of yielding a certain project return. Unlike other models, the average return of high-risk borrowers is lower than the average return of low risk borrowers.

What differentiates the outcome of Besanko and Thakor's model from that of Bester is the assumption of binding wealth constraints. With binding wealth constraints there are limits to which a low risk borrower can signal his creditworthiness using collateral (binding wealth constraints apply). Accordingly lower risk borrowers have their loans rationed. In other words, their loans are rationed because of the inadequacy of collateral under binding wealth constraints to testify to the borrower's lower risk. Put another way, collateral is unable to perfectly signal ex ante borrower creditworthiness and low risk.

It is important to note that the bank would prefer if low risk borrowers were not rationed. The only reason they are rationed is that the bank cannot ascertain their risk status ex ante. As Besanko and Thakor note;

'If the bank can perfectly sort borrowers into distinct risk classes based on observable differences alone, then there would not be any rationing'[7].

Any analysis of the theoretical literature would be incomplete without referring to the 'newer' theories of credit constraints that depart from some of the traditional assumptions of the older models or employ alternative approaches to investigating credit constraints. There is a tendency for the papers to advocate or warn against Government subsidisation of first-time borrowers and so the 'newer' theories are less detached from the policy implications of their model predictions than older models that do not caution against Government intervention.

De Meza and Southey (1996) depict entrepreneurs as relatively naïve participants in the lending contract while banks are comparatively well informed and able to use their information on the borrower efficiently. Drawing on the human psychology of risk they explore the consequences of a systematic bias in the population of entrepreneurs and conclude that the entrepreneurs most likely to receive loans under self-selection are the most optimistic. The meaning attached to the word 'optimism' is where the entrepreneur misconstrues or de-emphasises the inherent risks of his undertaking.

Because banks are aware of systematic optimistic bias, they do not attempt to separate borrowers but offer a pooling equilibrium with high interest margins and collateral requirements. The stringent terms demanded by the bank to start-up businesses that are meant to neutralise the losses arising from high loss rates, discourage the good risk pessimists from applying. The high-risk optimists will also regard the bank's terms as inordinately stringent because their assessment of their risk is so much at variance with the bank's assessment.

The model suggests that all types of first-period (start-up) entrepreneurs will therefore minimise their reliance on banks and instead opt for self-finance.

According to de Meza and Southey, credit constraints are justifiable in view of a systematic optimistic bias.

'Whereas the standard formulations suggest that credit markets lend too little....the obvious implication of the optimism story is that new entrepreneurs are drawn to business and excessive bank loans much as lemmings are drawn to the sea. Banks should be applauded for stemming the rush'[8].

This paper therefore finds that credit constraints are a consequence of entrepreneurial optimism and that they are entirely justifiable.

Another of the newer papers to make a contribution in the area of credit constraints is by Evans and Jovanovic (1989). One of the unusual features of the Evans and Jovanovic paper

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[7] P.678 Besanko and Thakor (1987a)

is its almost equal emphasis describing and testing the theory. Unlike any of the papers that have gone before it follows up the exposition of the theoretical model with an exercise that tests the model's predictions.

Evans and Jovanovic investigate whether individuals choosing to become first-time entrepreneurs are credit constrained. Individuals are predicted to face an L-shaped liquidity curve or credit constraint where individuals with high entrepreneurial ability but low assets are more constrained than individuals with comparable ability but higher initial assets. Individuals face two options; either they work in wage employment or they enter self-employment. Depending on their entrepreneurial ability, individuals with higher levels of 'business acumen' will seek to move from wage earning employment to self-employment where the total and marginal return on their entrepreneurial ability is higher. Then, depending on their starting level of assets they will be either credit constrained or not.

They find that almost all the entrepreneurs in their sample devoted less capital in their businesses than they would like to, given the marginal increase in earnings they would gain from the investment of additional assets. A 10 percent increase in business capital leads to a 2.2 percent increase in earnings.

They conclude that because businesses can only leverage 1.5 times their asset value in the form of outside capital, under-capitalisation of businesses arises and entrepreneurs have to recourse to friends and relatives to help them out financially. However, assets are only essential at the inception of the new business because their correlation with business income even becomes negative when the initial financing period has elapsed.

Their assertion that credit constraints exist, agrees with that of de Meza and Southey. However, unlike the latter, Evans and Jovanovic do not contend that entrepreneurs are justifiably denied sufficient capital by the bank. A major distinction between the two papers is that while de Meza and Southey assume that the bank's portfolio of first-time borrowers exhibits a high default rate, Evans and Jovanovic assume that there is no default loss because loans are either too small or are heavily collateralised. This feature of the two papers brings about opposing viewpoints regarding the justice of credit constraints. While de Meza and Southey observe no inefficiency in the credit market, merely entrepreneurial underestimation of the risks involved, Evans and Jovanovic conclude that subsidisation of business by Government is an imperative as a consequence of the shortfall in initial wealth of prospective entrepreneurs. They infer from their data that the existence of credit constraints deters 1.3 percent of the population of individuals from trying entrepreneurship.

[8] P.385 de Meza and Southey (1996)

8.4 Summary of the credit constraints models and their weaknesses

To sum up the theoretical work of credit constraints, it can be seen that past theories of credit constraints are far from unanimous on the nature and effectiveness of credit constraints in reducing lending risk to first-term borrowers. While Jaffee and Russell advocate a reduction of the amount loaned to each borrower until the risk category of the borrower becomes known, Stiglitz and Weiss indicate that this would raise rather than lower the risk profile of the loan portfolio because businesses would be undercapitalised. They suggest their alternative theory where a threshold interest margin, below the equilibrium rate, allows the bank to maximise its profits. The bank practises non-discriminative, lottery-style rationing and does not supply loans to the rejected applicants. The remaining applicants who are charged a low interest have no incentive to engage in excessive risk taking behaviour because the interest margin is kept artificially low and overall portfolio risk is reduced.

While Bester argues that banks can devise contracts that permit them to completely separate high from low risk borrowers, Besanko and Thakor argue that this is not possible because of wealth constraints. Credit rationing cannot be eliminated because of the inadequacy of collateral under binding wealth constraints to signal the creditworthiness of low risk borrowers. Instead the bank must resort to rationing good borrowers in order to dissuade bad borrowers from preferring the low-risk contract.

Evans and Jovanovic's model agrees with the verdict of Besanko and Thakor (1987b) that initial-wealth is binding. Unlike Besanko and Thakor they also empirically test their model and support the model predictions with empirical evidence. De Meza and Southey find theoretical evidence for credit constraints that arise from excessive borrower optimism that systematically distorts the risks of undertaking a business project. Accordingly, they conclude that credit constraints are a necessary evil. Unlike Evans and Jovanovic who argue for more State support of enterprise due to inefficiencies in the credit market, de Meza and Southey lay the blame for credit constraints squarely at the feet of the entrepreneurs themselves.

There are some weaknesses with the theories that I would like to raise here. Firstly, with assumptions of information asymmetry there is an emphasis on the loan contract variables such as collateral, interest margins and loaned amount that help the bank discriminate between high and low risk borrowers. The exception to this general pattern of omitting borrower-specific control variables is the encapsulation of control variables (work experience and educational attainment) in the entrepreneurial ability variable by Evans and Jovanovic (1989).

The undue emphasis on information asymmetry by the theorists, masks what is a more likely situation in practice. The reality of the lending environment means that the bank has more information at its disposal than the collateral, loan amount and interest margin variables. It also has recourse to credit bureau data, however limited, and in commercial borrowing situations the track record of the borrower on any non-commercial loans it has taken out in the past. The models generally fail to take cognisance of other information that is available to the bank and in so doing have concentrated somewhat excessively on the loan contract variables.

Secondly, a related weakness of the theory, the exception again being the Evans and Jovanovic (1989) paper, is the dichotomy between the theory and observed practice of credit rationing. The theories generally suffer from a lack of reference to empirical regularities. While the theories mean to simplify reality, the practice of not testing the theories on real data means that the general theories of credit constraints tend to be divorced from the risk assessment procedures performed by banks worldwide. Authors who derive new theories referring to credit constraints generally do not test them on real data.

A final problem relates to the mutual exclusivity of the TCR and ECR theories. It is not improbable that a bank practices both types of credit rationing simultaneously. The bank may employ above average rejection rates for first-time borrowers (ECR). However, the bank may also regard first-period lending as a period where the bank establishes the creditworthiness of the borrower and therefore lends a smaller loan than requested as a precautionary measure with amounts more in line with the borrower's expectations to be loaned in subsequent periods ('transitionary credit rationing').

8.5 Empirical evidence of credit rationing

The main empirical analyses of commercial credit constraints by Cressy (1996c) and Cole (1998) are now described[9]. In the evaluation of both studies, the primary issue of controlling for other information available to the banker when a loan application is under review is considered. The second criteria used here for evaluating an analysis is the interpretability of

[9] Cressy (1996a) also contains a theoretical model containing an adaptation of the Evans and Jovanovic (1989) model showing that survival should be positively influenced by human capital variables. Because of the paucity of empirical work, I have described it here

the findings. Since data relating to the rejection and acceptance of loans is difficult to access, other ways of inferring the existence of credit constraints have to be used.

Cressy (1996c) tries to discover whether small businesses are credit constrained. He does not examine credit constraints directly but instead measures the effects of financial factors, assets and human capital on the survival of small businesses. He regresses his explanatory variables against his response variable, indicating whether or not an account that was opened in the second quarter of 1988 had remained open until the first quarter of 1992.

His indirect methodology of inferring the existence of credit constraints when using survival as an outcome variable is the standard test of credit constraints when following the Evans-Jovanovic (1989) model .

'A testable prediction of the E-J model is therefore that if the probability of survival depends on assets, then capital constraints exist'[10].

The link between credit constraints and business survival has already been established empirically. Holtz-Eakin et al. (1994) discovered that entrepreneurs who received inheritances i.e. had higher initial wealth, were more likely to survive in business than the control group. His control group consisted of individuals who had received no wealth endowment. A $150,000 inheritance increased the probability of survival by 1.3 percent.

Cressy infers from the weak relationship he finds between financial variables and firm survival when human capital variables are controlled for, that credit rationing, if it exists at all, does not affect the survival of business start-ups. Human capital factors such as educational attainment are the only major variables, which are significantly correlated with the survival of businesses.

Cressy concludes that the supply of credit by banks is perfectly elastic and that any rationing is legitimate on the basis that the bank is only picking winners *a priori* because the best start-ups in terms of human capital are the ones that survive.

'Rationing exists but is human capital based and reflects the bank's desire to bet wisely'[11].

Cressy's HC (Human Capital) theory that was described under the *'switching models'* in **section 2.3** of **Chapter 2**, does not lend support to the debt-gaps findings of Evans and Jovanovic (1989) where the survival of firms is predicated by the amount of assets or wealth they have to offer the bank as collateral on borrowing. According to the Evans-Jovanovic model, assets should be positively correlated with survival if start-ups are credit rationed. The rationale for this test is based on the predicted correlation between assets and the

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[10] P.1256 Cressy, 1996a

[11] P.1254 Cressy, 1996c

likelihood of obtaining the optimal level of finance requested, if credit rationing operates. The corollary to this is that under-funded, higher quality firms are less likely to survive if a bank fails to supply them with the amount of finance they needed to realise their business project. Cressy (1996c) finds that higher quality firms, in terms of human capital, are more likely to survive and that these high quality firms are also more likely to receive finance. The bank can therefore 'pick winners'. Therefore, Cressy concludes that E-J rationing does not exist because a bank is able to differentiate between high and low quality firms. Where human capital variables enter his regressions, they cancel out any relationship between asset levels and survival. High quality firms are more likely to survive and they are also more likely to have higher levels of initial wealth.

The implication of Cressy's conclusion is that banks have enough information at their disposal to make wise bets as to the quality of firms. Rather than allowing an incentive compatible loan contracts to sort bad from good borrowers as we have seen described by Bester (1985) and Besanko and Thakor (1987b), the bank resorts to using the information it has to screen borrowers. In other words, banks know more about the borrower's quality than the literature gives them credit for. The information regime characterising bank lending is symmetric rather than asymmetric.

But a criticism of Cressy's paper is that his survival outcome variable, indicating whether or not an account was closed or not four years after the date of opening, is not an optimal measurement of survival. He notes this weakness in Cressy (1996c) when he acknowledges that a business may close its account for reasons other than business failure. It may be offered better rates elsewhere. A key assumption is therefore the correlation between account closure and business failure.

A further weakness of Cressy's research design is that his sample of businesses is not representative of the population of entrepreneurs who apply for loans. The estimation sample he used consists only of business start-ups that have been accepted by the bank. Therefore, businesses applying for finance, but which have had their applications turned down, are not represented in Cressy's estimation sample. The distribution of start-ups includes only businesses that have already passed the bank's criteria. It follows that the only ranges of the demand curve for finance being captured, are where demand is met by supply. Since constraints are a symptom of precisely this phenomenon where supply fails to satisfy demand, it follows that the estimation sample is not adequately representative of constrained firms and it is likely that he underestimates the magnitude of credit constraints. This is also an example where sample selection bias may occur (Heckman, 1979).

Despite the problems of sample bias, one of the major strengths of his analysis, which is unequalled anywhere else in the literature, is his inclusion of many variables representing the level and depth of information available to a loan sanctioner. The human capital variables include the entrepreneur's age, experience, academic education, vocational education, previous employment status and present employment status. The significance of these additional variables should indicate the extent of the bank's information at the time of application. A further strength of his analysis is his use of a four-stage estimation procedure allowing a system of simultaneous equations to sort out interdependencies among the variables. An example of these interdependencies arises where individuals with high human capital (ability) are more likely to be endowed with high levels of assets. However high human capital also influences survival as does the ability to leverage finance using assets.

Unfortunately, Cressy does not include any behavioural information (creditworthiness of entrepreneur on previous loans in a business or personal capacity). The lack of behavioural information, plays down the importance of pre-existing bank-borrower relationships and overestimates the importance of the application characteristics of the borrower such as the human capital characteristics[12]. The assumption that start-ups do not have a track-record, excludes potentially useful explanatory variables for credit rationing which would otherwise complete the list already comprising variables such as human capital, asset and loan factors[13]. Chakravarty and Scott (1999) investigated the likelihood that US households were credit rationed. They attempted to address the issue of asymmetric information between borrowers and lenders by hypothesising that asymmetric information is decreasing in the length of the borrower/lender relationship. It follows that the longer the relationship between the borrower and lender the less credit constrained a household would be expected to be.

In their empirical work they found that the relationship variables denoting the length of the borrowing relationship and another denoting the breadth of the relationship' were significantly negatively related to credit constraints.

[12] Cole (1998) uses bankruptcy as an explanatory variable for credit constraints and Chakravarty and Scott's (1999) analysis contains a dummy variable indicating whether a member of the family had difficulty in making payments over the past year. In my model, I include the behavioral variable *'fin_dif'* as my proxy for financial distress

[13] It can be argued that human capital characteristics such as age and vocational experience are exogenous to previous repayment performance. In this case human capital variables are likely to be collinear with past performance variables if both are used to explain the sanctioner's decision to grant a loan or not. This reasoning may well be correct, in which case Cressy's (1996a) model is not misspecified. However, the rationale underpinning the inclusion of such variables is to include as many of the variables informing the loan extension decision as possible in order to explain why certain loans are turned down.

However, the analysis by Chakravarty and Scott investigates US households and not small businesses. The same results do not necessarily obtain for small businesses. Nevertheless, there are similarities between this research and the small business literature. Chakravarty and Scott focus on asymmetric information and credit constraints, and refer to the theory on financial constraints between businesses and their banks and use a logit model to estimate the significance of their relationship variables on the existence of credit constraints.

A further study by Cole (1998) addresses the question of what motivates a bank to decline a small business loan. Cole uses a logit model to find that the likelihood that a small business has its loan application turned down is lower for a business which has a pre-existing relationship with the bank. The format of Cole's analysis is therefore very similar to that used by Chakravarty and Scott described earlier but the data relate to US businesses rather than US households.

Unlike Cressy, Cole's (1998) analysis does include firms that had their applications for finance rejected. It is, therefore, more likely to be representative of constrained firms. He argues that previous research has not addressed the disproportionate number of unconstrained firms in estimation samples. Cole notes that;

'This is a more comprehensive and intuitive test than previous studies...moreover it enables us to make inferences about firms denied credit as well as those extended credit' [14].

The most important outcome of Cole's analysis, is that a potential lender is more likely to extend credit to a firm which has a pre-existing relationship as a source of financial services (track record) but that the duration of this relationship is unimportant. A second finding of Cole's analysis, is that businesses which have several connections with other banks are more likely to be turned down on their credit applications. This latter finding supports banking intermediation theories postulating that the private information a bank accumulates on a business is less valuable when the business cultivates multiple ties with other banks.

To my knowledge, Cole's analysis is the only empirical analysis to date that has investigated the loan rejection decision. A drawback of Cole's analysis is that he does not control for human capital variables in his analysis. This means that he cannot define the quality of an entrepreneur's application in terms of variables measuring the continuity of the business, the shared decision making structure, the confidence of the entrepreneur, his age or work experience. Therefore, it is not as easy to infer from Cole's analysis that a small business is credit constrained because it could happen that the real reason that the bank rejected the small business loan was due to the poor quality of the entrepreneur's skills, his inexperience or lack of confidence. A business can only be said to be credit constrained if it merits more capital on the basis of the viability of its business project. Therefore, the viability of the entrepreneur's business project or human capital must be controlled for before a researcher can conclude that a small business is credit constrained.

An additional drawback with Cole's analysis as an empirical response to the theoretical literature on credit constraints, is that it is not aimed at analysing credit constraints in the context of asymmetric information. Unlike Cressy (1996c), who deliberately chooses a sample of start-up firms because of their lack of a track record and hence most adversely affected by problems of information asymmetry, Cole investigates a general set of firms. He does not set out to examine first time business borrowers or those without a track record with the bank. It is therefore possible that his conclusion that credit constraints do not exist is predicated by the under-representation of risky, first time borrowers in his estimation sample.

An argument in support of the general nature of Cole's sample is the average size of firms it contains. On average, firms which had their application for loans accepted had total sales of \$7,040,000 and the average sales of businesses which had been denied finance was \$1,530,000. Similarly, firms which had their applications accepted were on average 16 years old and their rejected counterparts 11 years old. Cole's analysis deals therefore with established firms. However, large and existing firms are the least likely to exhibit credit rationing as a result of asymmetric information problems and therefore the sample of businesses used by Cole is not ideal for testing theories of asymmetric information and their implications for credit rationing.

In the following sections I outline my research which aims to address some of the shortcomings in the existing research into credit constraints. The methodology uses the same approach as that used by Cole. However, the data used is similar to the data on business start-ups used by Cressy, where problems with asymmetric information should be most pronounced (for first-time business borrowers without a track record).

In the next section, I describe the data used in the subsequent regressions investigating the effect of my explanatory variables on credit constraints.

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[14] P.976

8.6 The dataset and description of the variables

As in my previous chapter on the role of entrepreneur-bank relationships (**Chapter 7**), I describe the main variables affecting the decision to grant a loan to a first-period borrower as relationship, credit history, loan contract or human capital variables. The emphasis in empirical work so far has been on the role played by the former two groups, relationship and credit history. To date, there is no direct empirical analysis of the influence of human capital and loan contract variables on the decision to grant a small business loan. Therefore, I concentrate on exploring the hypothesised relationships between human capital and loan contract variables with a bank's decision to reject a first-period business loan.

A summary of all the predicted signs of the variables employed in my analysis is contained in **Table 8.1**.

Human capital variables

I first turn to the potential importance of human capital variables to the bank's appraisal of the firm. The reason I emphasise the importance of these variables is twofold. The first and most important reason is that only by controlling for these variables can a researcher ascertain whether a small business is credit constrained or not. You will recall from the previous section, that a drawback of Cole's study was that it did not control for human capital variables. Therefore, the reason why the bank rejected a small business loan could be due to low project or entrepreneur quality rather than the necessity to limit funds to the business because of asymmetric information.

Intuitively we know that the appraisal of business start-ups is similar to the appraisal of individuals. This is because the creditworthiness of a business start-up is dependent on the creditworthiness of one or two key individuals (Mester, 1997).

Cressy (1996c) finds that human capital variables such as group capital, where the business ownership structure is dispersed and hence the firm benefits from a wider skills base, and the entrepreneur's age are highly related to the survival of business start-ups. If banks are cognisant of the importance of 'picking winners', it is reasonable to assume that a priori good entrepreneurs who are rich in human capital have a higher chance of obtaining credit than entrepreneurs who are lacking in these attributes. Therefore, I include an ownership dispersion proxy *'partner'* and business continuity proxy *'busoper'* because businesses with broader ownership structures and whose succession is assured are less likely to fail and hence are more likely to obtain credit (Burns and Clements, 1992; Bopaiah, 1997; Cressy, 1996c)[15]. I also include a variable indicating whether the entrepreneur's description of his business activities was corroborated by bank personnel visiting his business premises, *'businl',* as a check of the veracity of the entrepreneur's replies. Consistent with Cressy's discovery that an entrepreneur's age and survival are positively correlated, I include the variable *'age'* but also a squared term to capture potential non-linear effects. Borrower experience is captured in the variable *'exp'* and I again include a squared term. I hypothesise that business cash flow captured in the variable *'liq1'* also informs the bank's decision on the basis of its high correlation with business survival (Bahnson and Bartley, 1992; Gilbert et al., 1990; Platt and Platt, 1990; Platt et al., 1994, Schellenger and Cross, 1994; Taffler, 1999). I expect that the sign of the coefficient of the growth proxy *'growth1'* shows that higher growth is associated with a higher rejection likelihood because excessive early growth drains the enterprise of cash flow thereby inducing failure. The final human capital variable *'norisk'* indicates borrower confidence by signifying that the firm faces no risks. If entrepreneurs are telling the truth, this variable should be negatively related to the likelihood of rejection.

Moving on to the topic of loan contract terms, my hypothesised sign for the relationship between collateral level and the bank accept/reject decision is indeterminate. Cressy and Toivanen (2001) found that collateral is independent of risk type while Berger and Udell (1993) found that riskier firms were more frequently asked to provide collateral. The relationship between the amount of finance requested and the rejection decision is also indeterminate because although a bank seeks to reduce its exposure to first-period borrowers according to Jaffee and Russell (1976), Stiglitz and Weiss (1981) argue that this under investment in the entrepreneur makes him riskier as a result. Finally, interest margins were not included as loan contract variables because they are set after the bank has reached its decision to lend to the firm or otherwise[16].

As already indicated, **Table 8.1** shows a summary of the hypothesised relationships for all the variables in my data with the bank's decision to grant first–period finance.

The response variable (*'con'*=1)

It should be pointed out that the response variable that I use (*'con'*) denotes whether the bank rejected a commercial loan. However, *'con'* can also has a value of one when the

[15] These group capital variables, *'busoper'* and *'partner'* were also included in **Chapter 7** investigating the price of credit

entrepreneur rather than the bank turned down the loan. Therefore, it has a dual meaning which leads to ambiguities when the supply schedule (bank rejects the loan) cannot be differentiated from the demand schedule (entrepreneur rejects the loan). Despite this ambiguity, sources at the bank have indicated that the majority of loans that are turned down, are turned down by the bank and not by the business[17].

My credit constraint measure replicates the credit constraint proxy used by Cole (1998). The measure used in the following analysis distinguishes between borrowers who have had their applications rejected or accepted by their bank, given that some but not all have previously borrowed in the past in a personal rather than business capacity. In Cole's study, businesses have had a business track record with the bank.

Unlike Cole (1998), the businesses used in my sample have not been borrowing from the bank in a business capacity before. Some of these businesses have been borrowing in a personal capacity and therefore have a personal rather than business track record. Therefore the entrepreneurs in my sample may have established entrepreneur-bank relationships prior to applying for their first business loan[18]. This distinction is necessary because the borrowers in my sample are more likely to be representative of businesses who are adversely affected by information problems. This is because the bank has little idea how these start-ups will perform. The businesses in Cole's data are less likely to be affected by asymmetric information problems because they have an established business track-record, are relatively large on average and hence are likely to have higher quality financial information. Therefore, Cole's conclusion that credit constraints are unaffected by the length of a borrowing relationship for a sample of established firms, may not be applicable to the firms in my sample.

The question now turns to the extent of bank information on the past repayment performance of businesses in my sample. There is little public information available to the bank on the start-ups in my sample since they have not been in existence for very long and are non-listed companies. There is possibly more public information available on the transferred businesses, although they represented a small minority of businesses. Given that the lack of a track record applies to all members of the small businesses in my data, it is

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[16] See **Chapter 7 section 7.7**

[17] Cressy (1996a) experienced the same problem distinguishing between loans turned down by the business (non-rationing) and those by the bank (rationing). He found that businesses requesting finance and not taking up their loans comprised only 4 percent of his sample implying that the majority of loan rejections are initiated by the bank (credit-rationing)

[18] See **Chapter 7 section 7.2** for a description of *entrepreneur-bank* relationships and how they are different from *business-bank* relationships

relatively homogeneous. Applications were either placed for loans, overdrafts or other non-specified loans. The bank set the terms of the loans including the amount of collateral required and the amount of the loan were set before the decision was taken to decline or accept the loan.

The relationship variable (*'prevbor'=1*)

Consistent with other empirical work which proxy bank-borrower relationships, I have aimed to give a measure of how long the borrower has been with the bank. Unfortunately, the data does not indicate when the borrower commenced the bank relationship. Even if the data did show the day on which the relationship began, it could be argued that this information is of limited value. An entrepreneur can wear many hats; spouse, brother, private borrower or business borrower. Given that businesses may begin a non-business borrowing relationship before they open a business account, there is often pre-existing information on the borrower before the official date on which the connection is opened. With small businesses, it is not sensible to separate the performance of the business from the performance of the business owner because the owner *is* the business and his private and business finances are interrelated[19].

The dummy variable, previous borrowing (*'prevbor'*=1) which was already described in **Chapter 7**, indicates whether the entrepreneur had borrowed from the bank at some stage prior to applying for his first business loan. Unlike Cole's analysis, this previous borrowing denotes existing <u>consumer or personal</u> rather than business borrowing because the high-risk classified businesses in my sample are businesses without a <u>business</u> track record. Inability to demonstrate a business track record does not preclude businesses from having a track record that relates to their personal borrowing e.g. for a mortgage or personal current account. Therefore while Cole's relationship variable indicates the existence of a *business-bank* relationship, my relationship variable signifies a pre-existing *entrepreneur-bank* relationship.

Relationship variables in general are expected to play a significant role in explaining whether a loan was rejected or not. The likelihood that the bank turns down a business loan is expected to be negatively related to the relationship variable *'prevbor'* because the bank already knows the credit status of a small business that has previous borrowings. The outcome of Cole's analysis, demonstrated that the length of a relationship is not significant in explaining rejected loans. However, the probability the bank rejects an application for finance from an existing customer is lower than the rejection probability for a 'through-the-door' customer.

8.7 Model specifications and methodology

The fundamental question of my analysis aims to answer is: what variables are the most significant in predicting whether a loan was turned down or not?

Like Cole (1998), I use a logistic regression specification to model the relationship between the ex post likelihood that the bank rejects a first-period business loan. The model for credit constraints, *'con'* is $Con_i=1$ for a rejected borrower (has had application rejected) and $Con_i=0$ otherwise. For the logistic regression let

$Pr\,(Con_i=1) = G(Z_i), \;\; \forall i = \;\; \{1,2\},$

Where $pr\,(Y_i=1)$ denotes the probability of $Y_i = 1$,

and $G(Z_i)$ is the corresponding cumulative logistic function defined as

$G(Z_i) = 1/(1+e^{-Z_i})' \; \forall_i = -\infty < Z_i < \infty$

and

$$Z_i = \alpha + \sum_{j=1}^{1} \beta_j x_{ij} + \sum_{j=2}^{6} \beta_j x_{ij} + \sum_{j=7}^{7} \beta_j x_{ij} + \sum_{j=8}^{17} \beta_j x_{ij} + \sum_{j=18}^{18} \beta_j x_{ij} + \varepsilon_i$$

Where

$_{j=1}$ is my relationship proxy

$_{j=2-6}$ are my loan contract variables (including squared terms to check for non-linearities)

$_{j=6}$ is my size proxy

$_{j=8-17}$ are human capital variables (including squared terms to check for non-linearities)

$_{j=18}$ is my risk variable

ε_i is the stochastic error

8.8 Descriptive statistics

Table 8.2 outlines the univariate statistics for the relationship, loan contract, size, firm/entrepreneur specific and credit history variables used in my analysis.

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[19] This assumption is corroborated by Petersen and Rajan (1994) when they conclude that the reputation of the owner is more important than the firm's reputation

Column 2 describes the mean value for the group that was denied credit by the bank in each case. Alternatively, in the case of dummy variables, **Column 2** indicates the proportion of firms within the category of the variable that was denied credit. These individual proportions for separate dummy variables can then be compared to the overall rejection rate of 28.4 percent. **Column 3** likewise describes the mean amounts or proportions for each of the separate explanatory variables that will later be used in my estimations. In this instance, the proportions are compared to the overall accept rate of 71.6 percent. **Column 4** contains the significance levels and test statistics for each of the variables in the table.

We can see from **Table 8.2** that the most significant variables are the relationship and the loan contract variables. However some of the firm/entrepreneur characteristics are also significantly associated with the sanctioning of finance.

Of the significant variables, if a borrower has borrowed finance previously from the bank for his own personal use ('*prevbor*'=1), it enhances his probability that he will receive funding for his business. The proportion of accepted applicants within the category of borrowers with existing borrowings is 81 percent compared with an overall acceptance rate of 71.6 percent.

Firms that are extended credit are more likely to request smaller amounts. The difference in the means of £9,682 is significant at the 0.01 level. Firms who are successful on their loan applications are also more likely to provide higher collateral. The difference of £6,293 in the value of collateral is also significant at the 0.01 level. We can conclude therefore that a sanctioner is more likely to accept credit applicants where the bank's exposure to the possibility of default is minimised i.e. the credit amount is comparatively low and the collateral level is comparatively high.

Consistent with the cautious approach employed by the bank that we have seen in its preference for low risk loans, is the slight but significant preference for non-working capital loans which is significant at the 0.10 level.

Turning to the firm/entrepreneur characteristics that significantly affect the decision to deny credit; the self-assessment by the entrepreneur of his own risk is highly significant. More sanguine entrepreneurs who see no risks that would jeopardise their business projects, are more likely to receive credit than entrepreneurs who demonstrate self-financing capability. Finally, the bank shows a marked preference for businesses who can operate in the absence of the principal owner as evidenced by the higher proportion (73 percent) of applicants in this group who receive finance.

There is only one variable, namely credit history, in the last group and this is significantly related to the credit granting decision. Firms who have demonstrated financial difficulty in the past, *'fin_dif'*=1, are significantly less likely to receive credit than firms who have an unsullied credit history.

Overall, the univariate statistics point to the fact that the bank is cautious about the extent of its exposure to the risk of the business. However, it responds positively to a business who is in a position to finance a portion of the project, who is confident of the outcome of his project and who can assure the bank that the business can continue to manage its daily operations in the owner's absence.

8.9 Regression results

We now move on to the first regression that estimates the relationship between the four main categories of explanatory variables and the probability that an entrepreneur has his credit application turned down. In other words, I model the likelihood that *'con=1'*. The results are shown in **Table 8.3**.

Column 1 describes the model when I include the business-bank relationship variable, *'prevbor',* on its own. Consistent with what we have already seen in the univariate statistics, *'prevbor'* is highly statistically significant and has a negative sign. This indicates that entrepreneurs with existing borrowing are less likely to have their applications for finance rejected by the bank. The pseudo r-squared value of 0.009 is low. Nevertheless, as the χ^2 statistic indicates, the overall model is statistically significant.

Column 2 indicates the regression model of the accept/reject decision after the loan contract variables are added. Once again, consistent with what we have already seen in the univariate statistics, the higher the value of collateral provided, the lower the probability that an applicant will have his application for finance rejected, as indicated by a negatively signed coefficient. This confirms evidence from Basu and Parker (2001) that entrepreneurs in their sample attributed the lack of sufficient security as the main reason their credit application was turned down by a bank. However, there appears to be diminishing returns to collateral provision, as suggested by the positive sign on the coefficient of the variable *'coll2'*.

The larger the amount requested by the borrower, the higher the probability that a borrower's application will be declined by the bank, as evidenced in the positive sign and significance of the coefficient of the variable *'borr'*. Corroborating what we have seen earlier in the univariate statistics, loans for working capital purposes are more likely to be turned down.

In **Column 4**, I include the size control variable *'proj_sal'* but this is neither significant nor does it affect the model fit.

The results in **Column 4** describe the effect on the regression outcome when the entrepreneur/firm specific variables are added to the model. The pseudo r^2 increases to 0.024.

Consistent with Burns and Clements (1992) and Bopaiah (1997) comments on the importance of succession issues in small businesses, the coefficient of the variable *'busoper'* indicates that businesses whose succession is assured, are less likely to have their loans turned down. Business borrowers who have reinvested capital in their business or partially financed their projects using their own funds, are also less likely to have their loan requests turned down. Also entrepreneurs who are confident that their businesses face no risks, are more likely to be successful.

Finally in **Column 5** I include the credit history variable *'fin_dif'* indicating whether the business owner exhibited insolvency in the past or had his borrowings rescheduled. The pseudo r^2 increases to 0.026. As we would expect, applicants who have experienced financial difficulty in the past are significantly less likely to be granted a loan.

The most important outcome conclusion I draw from the analysis, is that there is evidence that the bank is keen to minimise its exposure to a small business. However, it is likely to reward new business borrowers who have existing accounts with the bank as evidenced by their higher likelihood of obtaining credit. The reason for this could be high information retrieval costs. Obtaining credit bureau data in order to judge an applicant's creditworthiness is costly. However, the information that a bank has already gathered about its existing customers is useful if they apply for a business loan. Because the creditworthiness of any individual who applies for a new business loan has an important role in informing the sanctioner's decision, it follows that a bank must deem the borrower's personal credit history as of high importance for a business loan.

A separate issue concerns the strength of the small business in terms of its liquidity, its ownership structure and the mindset of the entrepreneur. New businesses who are in a position to make a contribution towards the costs of their project i.e. are to some extent self-financing, are more likely to receive finance. Similarly, businesses with ownership structures guaranteeing continuity in the absence of the business loan applicant and entrepreneurs who are confident about the riskless nature of their venture, are preferred by loan sanctioners.

8.10 Individual variables explaining the bank accept/reject decision

When interpreting the value of the coefficients in a logistic regression I refer to the odds ratios because these reflect the most accurate measure of the individual contribution of the variables although the standardised coefficients can be used for ranking the variables in order of their relative importance (Allison, 1999). **Table 8.4** describes the marginal effects of the individual explanatory variables on the sanctioner's decision.

Column 1 in **Table 8.4** lists the beta values for the regression. In **Column 2**, the odds ratio for each of the explanatory variables is calculated. The odds ratio i.e. the ratio between the probability of being rejected and the probability of being accepted, $(P_{REJECT}\,(1 - P_{REJECT}))$, is calculated by obtaining the exponent of the beta values. In order to derive the values in **Column 3**, I first of all calculate the base odds ratio from the regression coefficients in order to provide a baseline against which I can measure any marginal effects. This baseline value (base odds ratio) is calculated by substituting back the averages of the continuous variables and setting the dummy variables equal to zero. The exponent of the resulting value is the base odds ratio which is found to be equal to 0.4877. This in turn is multiplied by the odds ratio in order to obtain the change in the base odds ratio for when the dummy variables are equal to 1 or the continuous variables increase/decrease by £100,000.

In **Column 4** I convert the modified base odds ratio when the marginal effect is included to a rejection probability, P_{REJECT}, for that variable. Finally, in **Column 5**, the change in rejection probabilities from the baseline probability of approximately 33 percent is calculated as $P_{REJECT} - P_{BASE}$ in order to demonstrate how entrepreneurs possessing this attribute exhibit rejection probabilities that differ from the baseline rejection probability.

We see in **Table 8.4** that the relationship dummy, *'prevbor'*, is the single most important variable in the regression where applicants for finance are 12 percent less likely to have their applications turned down if they have banked with the lender before. This result corroborates the importance of previous borrowing relationships testified by Cole (1998). However, I expand on Cole's analysis by noting the marginal effect of previous borrowings on the rejection probability. The marginal effects of different variables on the sanctioner's decision are now described in order of the magnitude of their effect.

Applicants retaining a profit or ploughing their own equity into a business project (*'liq1'*=1), are almost 8 percent less likely to be rejected compared with the baseline probability level. Hence the bank values the self-financing capability of new commercial borrowers.

Commercial borrowers who have had previous borrowings rescheduled due to an inability to meet repayments or who have been insolvent in the past, (*'fin_dif'*=1), are 5.8 percent less likely to have their applications accepted.

The role of entrepreneurial self-confidence is evident in the fact that applicants who state on their application forms that they do envisage that any risks lie ahead that would threaten their project (*'no_risk'*=1), are 4.3 percent more likely to obtain finance. De Meza and Southey (1996) have documented some of the theoretical considerations relating to entrepreneurial self-confidence and have concluded that the most risky entrepreneurs are not only likely to be more confident but also likely to be more successful in applying for finance. We cannot infer from this result whether these entrepreneurs are higher risk but we can conclude that more confident entrepreneurs are more likely to have their applications accepted.

A slightly worrying outcome is that applicants applying for working capital finance, *'working'*, are 3.6 percent more likely to be rejected than applicants whose borrowing purpose is for asset backed finance even when collateral has been controlled for. The problem is that liquidity constrained borrowers with good growth prospects may find that this constraint bites. However, one could argue that this marginal effect is small enough to be negligible and what really matters is relationship, clean track-record and an ability to be self-financing.

It is evident that a bank is cognisant of business continuity issues when sanctioning a loan to a new commercial borrower. Business owners who indicate that their business can continue to operate in their absence, *'busoper'*=1, are associated with lower rejection probabilities[20].

The loan contract variables *'coll'* and *'borr'* do not individually lead to a dramatic change in the likelihood that a loan is accepted/rejected. Borrowers providing £100,000 additional collateral are approximately 4 percent less likely to be rejected compared with the baseline acceptance probability. Applicants who request £100,000 more are associated with a relatively higher rejection probability i.e. a 2.9 percent differential.

Factors like the entrepreneur's age and work experience, while significant in explaining the price of credit as Hanley and Crook (2001b) demonstrate, do not appear to influence the sanctioning decision.

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[20] It appears contradictory that the variable *'partner'* indicating that the business ownership comprises at least one owner is associated with a higher rejection likelihood. The business continuity variable *'busoper'* has the expected negative sign and *'partner'* was similarly expected to reduce the rejection probability. Our explanation for this anomaly is that a sanctioner may be marginally inclined to favour loans over which it has greater control and increasing the number of partners may decrease the strength of the relationship between the applicant and his contact at the bank.

8.11 Conclusions and implications of analysis for relationship lending

It is evident from these estimations that relationship, loan contract and some entrepreneur/firm variables are important inputs in the sanctioner's decision to reject a loan to a new commercial borrower. Increasing the amount of collateral provided and reducing the amount of finance requested, increases the likelihood that a loan will be granted. This indicates that the bank prefers lower risk exposures to higher exposure, all things equal. This outcome is consistent with my expectation that a bank is a rational, risk adverse agent.

I conclude that a bank emphasises the value of pre-existing relationships, borrower credit history and the ability of a borrower to be self-financing when granting a loan. However, the fact that a borrower has banked with the lender before, is by far the most important factor to elicit a positive sanctioning response from the lender.

The implication of this finding that entrepreneur-bank relationship and credit history variables play an important role in the sanctioning of finance to new business customers is profound. A prospective new business borrower seeking finance for his new business venture has a greater chance of succeeding if he already has some type of existing MTA (Money Transmission Mechanism) account such as a student or adult current account[21]. If he does not exhibit adverse behaviour, such as overdrawing on this account and delaying the repayment of these excesses, he runs the risk that this adverse repayment behaviour on *personal borrowings* will jeopardise his application for *business borrowing*. Therefore, in the absence of information that would describe the business' track record, a bank defaults to the next best alternative which is its own store of in-house information albeit relating to a *personal* rather than *business* track-record. New corporate borrowers, particularly those seeking start-up finance where the credit history of the owner is of key importance, would be advised not to underestimate the importance of their existing MTAs when applying for a first time commercial loan.

[21] An MTA is a dynamic account that is used for credit scoring purposes because it allows a banker to identify how often, by how much and for how long a customer has exceeded his account limit. It is therefore a useful indicator of customer quality

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Table 8.1 List of variables

Response variable	Description	Predicted sign
con=1	The loan is rejected by the bank	.
Relationship		
prevbor	*prevbor* =1 if applicant has previously borrowed from the bank	(-) Lummer and McConnell (1989) (.) Billett et al. (1995)
Loan contract		
coll	Sum of owner's equity injected into the project in addition to the 'carcase' or liquidation value of land, buildings and life policies offered as collateral	(?)
coll2	Collateral squared	
borr	Amount of new borrowing requested. Sum of loan, overdraft and any other amounts requested	(?)
borr2	Borrowing squared	
working	Borrowing used to finance working capital. Most risky type of borrowing as no purchased asset to submit as collateral against borrowed amount	(+) Berger and Udell(1995)
Size variable		
projsal	Projected sales for the current year (size proxy)	
Human capital		
partner	The business owner has at least one business partner i.e. the ownership structure is dispersed	(-) Burns and Clements (1992) (-) Bopaiah (1997) (-) Cressy (1996) according to 'group capital' hypothesis
busoper	The business can continue to exist without the founder. Measure of dispersion of ownership (busoper=1 if 'Yes')	(-) as for *'partner'*
liq1	Proxy for the ability of the entrepreneur to be self-financing. Liq1=1 if the business has reinvested profit in business or injected its own cash into the business project	(-)Schellenger and Cross, 1994; Taffler, 1999
growth1	Sales growth. Percentage change in sales from last year's sales	(+) See liq1
age	Borrower's age	(+) related to survival (Cressy, 1996)
age2	Borrower's age squared	
exp	Experience of borrower in current industrial sector	
exp2	Experience of borrower in current industrial sector squared	
norisk	Borrower believes that he will have no business or financial risks in the year ahead. Denotes borrower confidence (norisk=1 if 'Yes')	(-) if information is symmetric and entrepreneur is telling the truth
Credit history		
fin_dif	Borrower has had to have his loan rescheduled due to difficulties meeting repayments or has previously been declared insolvent. Denotes financial distress if debtres=1.	(+) Cole (1998)

Table 8.2 Univariate Statistics

(1) Variable	(2) Firms denied credit	(3) Firms extended credit	(4) t-statistic/ $\chi 2$ statistic
Number of firms	1,695	4,273	
Proportion of firms	**28.4%**	**71.6%**	
Business-bank relationship			
Entrepreneur has previous borrowings (*prevbor*=1)	19%	81%	65.394[a]***
Loan contract terms			
Amount borrowed	76,679	66,997	-3.166[b]***
Amount of collateral	52,549	58,842	1.744[b]***
Loan purpose is working capital (*working*=1)	29.4%	70.6%	3.192[a]*
Size			
Sales	265,250	309,506	0.296[b]
Firm/entrepreneur characteristics			
Entrepreneur's age	43.3	43.5	0.582[b]
Number of yrs. work experience	12.7	12.5	-0.821[b]
Business owner has business partner	29%	71%	1.055[a]
Business sees no risks ahead (*norisk*=1)	26%	74%	19.058[a]***
Firm growth (projected sales/present sales)	5.31	5.85	0.251[b]
Ability to self-finance (has retained a profit or invested own capital) (*liq1*=1)	26%	74%	40.809[a]***
Continuity of business is assured (*busoper*=1)	27%	73%	9.241[a]***
Credit history			
Financial difficulty (*fin_dif*=1)	33%	67%	15.572[a]***

[a] denotes $\chi 2$ statistic (difference in proportions)
[b] denotes t-test (difference in means)
*** difference in means of groups or proportions significant at the 0.01 level
** difference in means of groups or proportions significant at the 0.05 level
* difference in means of groups or proportions significant at the 0.10 level

Table 8.3 Logit to determine relative importance of variable groups in accept/reject decision

Response variable: *P(con)=1*: applic. Rejected (Prob. > $\chi 2$)					
	(1)	(2)	(3)	(4)	(5)
Intercept	-.8137***	-.9064***	-.9064***	-1.0098**	-.9444***
	(.0000)	*(.0000)*	*(.0000)*	*(.0261)*	*(.0378)*
Business-bank relationship					
prevbor	-.6526***	-.6214***	-.6214***	-.6665***	-.6430***
	(.0000)	*(.0000)*	*(.0000)*	*(.0000)*	*(.0000)*
Loan contract terms					
coll		-1.8E-06***	-1.8E-06***	-1.7E-06***	-1.9E-06***
		(.0001)	*(.0001)*	*(.0003)*	*(.0001)*
coll2		9.48E-13**	9.48E-13**	8.83E-13*	9.87E-13**
		(0.0412)	*(.0413)*	*(.0581)*	*(.0344)*
borr		1.28E-06**	1.28E-06**	1.48E-06**	1.30E-06**
		(.0321)	*(.0321)*	*(.0129)*	*(.0307)*
borr2		4.58E-13	4.58E-13	1.05E-13	3.14E-13
		(.6075)	*(.6076)*	*(.9042)*	*(.7202)*
working		.1359**	.1359**	.1672***	.1594***
		(.0239)	*(.0239)*	*(.0062)*	*(.0092)*
Size					
projsal			-1.2E-10	3.06E-10	2.47E-10
			(.9866)	*(.9645)*	*(.9718)*
Firm/entrepreneur characteristics					
partner				.0901	.0818
				(.1296)	*(.1699)*
age				.0281	.0254
				(.1783)	*(.2251)*
age2				-.0003	-.0003
				(.1322)	*(.1505)*
exp				-.0016	-.0019
				(.8424)	*(.8142)*
exp2				.0001	.0001
				(.5819)	*(.5282)*
busoper				-.1428**	-.1577**
				(.0466)	*(.0282)*
norisk				-.1964***	-.2019***
				(.0011)	*(.0008)*
liq1				-.3892***	-.3845***
				(.0000)	*(.0000)*
growth1				5.05E-05	6.91E-05
				(.8992)	*(.8622)*
Credit history					
fin_dif					.2523***
					(.0006)
-2 log likelihood					
Intercept	7052.50	7021.63	7021.63	6953.49	6941.81
$\chi 2$ for covariates	69.766	100.64	100.642	168.776	180.464
DF $\chi 2$ for covariates	1	6	7	16	17
Sig. for covariates	.0000	.0000	.0000	.0000	.0000
Pseudo-r^2	0.00989	0.0143	0.0143	0.024	0.026
Number of observations	5,968	5,968	5,968	5,968	5,968
***sig. at 0.01 level		** sig at 0.05 level		*sig. at 0.10 level	

Table 8.4 Marginal analysis; effect of individual variables on the bank rejection rate

	B	Odds ratio *(exp(B))*	Odds ratio* base odds ratio[1]	P_{REJECT}[2]	Difference in rej. rates[3]
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.9444				
prevbor	-0.6430	0.5257	0.2564	0.2041	-12.4%
coll *(00,000)*	-0.1900	0.8270	0.4033	0.2874	-3.98%
borr *(00,000)*	0.1300	1.1388	0.5553	0.3571	+2.9%
working	0.1594	1.1728	0.5719	0.3638	+3.6%
projsal *(00,000)*	2.47E-10	1.0000	0.4877	0.3278	0.0%
partner	0,0818	1.0852	0.5292	0.3461	+1.8%
age	0.0254	1.0257	0.5002	0.3334	+0.6%
age2	-0.0003	0.9997	0.4875	0.3277	0.0%
exp	-0.0019	0.9981	0.4867	0.3274	0.0%
exp2	0.0001	1.0001	0.4877	0.3278	0.0%
busoper	-0.1577	0.8541	0.4165	0.2940	-3.4%
norisk	-0.2019	0.8172	0.3985	0.2849	-4.3%
liq1	-0.3845	0.6808	0.3320	0.2492	-7.9%
growth1	0.0001	1.0001	0.4877	0.3278	0.0%
fin_dif	0.2523	1.2870	0.6276	0.3856	+5.8%

[1] The base odds ratio = $exp(B_i\ \mu_{ij}) = 0.4877$

[2] P_{REJECT} = base odds ratio * odds ratio$_i$ / [1 + (base odds ratio * odds ratio$_i$)]

[3] P_{BASE} = *base odds ratio/ (1 + base odds ratio)* = 0.3272 or 32.7%
Difference in reject rates = $P_{REJECT} - P_{BASE}$

Chapter 9

Collateral levels for existing businesses and first-period business borrowers[1]

[1] A shortened version of this chapter is available as Hanley (2002). *'Do binary collateral outcome variables proxy collateral levels? The case of collateral from start-ups and existing SMEs'*. Small Business Economics, v18, pp. 317-331

9.1 Introduction

Previous chapters have dealt with the availability and price of credit. This final empirical chapter looks at collateral level issues. This chapter not only investigates the level of collateral provided by entrepreneurs from business start-ups. It also compares collateral levels for new business borrowers with the magnitude of collateral that is provided by existing business borrowers.

This is the first empirical analysis contrasting the collateral levels required from new viz. a vis existing borrowers. A previous analysis has investigated the likelihood that collateral is required from businesses as a function, inter alia, of the business-bank relationship, duration of the loan and size of the firm (Cressy and Toivanen, 2001). Other analyses have compared the likelihood that various types of collateral are required on overdraft finance only (Berger and Udell, 1995; Cressy, 1996a). However, no analysis has directly compared the collateral levels required on bank lending for new vis a vis existing firms respectively.

This is also the first analysis to compare the results obtained using two different definitions of the collateral variable; a binary variable indicating whether collateral was required or not and a continuous variable indicating the level of collateral. Therefore, this analysis is the first to investigate whether a binary '*yes_no*' type variable leads to the same conclusions about the role of the independent variables as the variable measuring collateral level that I have used in analyses so far '*allcoll*'. If the analysis using the binary response variable yields results similar to the analysis on collateral level, there is a rationale for proxying collateral level using a simple binary variable. Such a proxy would be very useful for further research where there is comparative difficulty quantifying the amount of collateral on loans.

An additional feature of this analysis is that it also controls for the <u>level of borrowing</u> and thus measures the effect of borrower type on collateral level per unit of finance borrowed. Therefore this analysis looks at the level of bank exposure to the firm rather than looking at collateral in isolation without controlling for the amount of finance borrowed[2].

I find that new business borrowers are charged less collateral than existing borrowers. However, this result is qualified by an artefact of collateral data, where the indivisible and cumulative nature of collateral make pricing to risk or business type difficult to implement in reality.

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[2] Cressy (1996a) includes the level of <u>allowable</u> borrowing in the form of the overdraft limit as an explanatory variable in his regression estimating whether collateral is demanded or not. Cressy and Toivanen (2001) have a measure of loan size but do not derive collateral to loan value ratios or control for borrowed amount in their estimation.

The structure of this chapter is as follows. I first of all outline the central issues relating to collateral and where I have sought to address some of these issues in the next section. The sections following this deal with the theoretical and empirical literature respectively. In the next section, I describe the data, introducing for the first time the new dummy variable distinguishing between business first-period business borrowers and established business borrowers. This is followed by the methodology before I present my results. My results section comprises some descriptive statistics and the results of my estimations. I then present my conclusions before giving the implications of my findings for future research.

9.2 Key collateral issues

The issue of collateral is central to the debate on the provision of finance to small businesses. In a general sense, there is a limit to which interest margins can be used to neutralise the risk of lending to a risky borrower due to the Stiglitz and Weiss (1981) adverse selection effects that were described in **Chapter 2**[3]. This means that a bank becomes more reliant on collateral to produce motivation in the borrower who knows he will lose his collateral if he defaults (Jaffee and Stiglitz, 1990). Collateral can also be expected to diminish the likelihood that the borrower will take excessive risks (moral hazard).

In general, the importance of collateral is underpinned by a number of key issues. The first issue concerns the central role of the collateral to loan value ratio in influencing the number of individuals who choose to set up their own business. Collateral therefore has important microeconomic implications. I have already highlighted in **Chapter 2** the role that is played by collateral in the *'switching theory'* by Evans and Jovanovic (1989) that was further developed by Cressy (1996b) to include human capital. According to this theory, if a more favourable lending to assets ratio employed by the bank induced an entrepreneur to switch from waged-employment to self-employment, then credit rationing exists. If a more favourable bank lending to assets ratio induced entrepreneurs to enter self-employment, then the level of collateral demanded by banks plays a significant role in determining the level of entrepreneurship in the economy.

The second issue concerns the role of collateral when the bank is unsure of the borrower's risk status due to asymmetric information. If a viable small business is confined to leveraging bank debt in direct proportion to its existing assets, then, ceteris paribus, asset-poor start-ups are penalised relative to asset-rich existing businesses that have accumulated wealth over the number of years that their business has been in operation. Moreover, if collateral is used to defray against the risk of bankruptcy and new businesses have a higher likelihood of going bankrupt, it follows that new businesses are likely to leverage even less debt in proportion to the magnitude of their asset base than existing businesses who have a lower a priori risk of failure. This conclusion would be actuarially fair (justified on the basis of increased risk) if the bank's appraisal of small business risk were correct. In this case new businesses, being higher risk, would be charged appropriately higher collateral levels. If the bank's judgement is distorted due to asymmetric information, then an actuarially unfair situation would emerge whereby newly founded businesses would be penalised by being asked to provide relatively more collateral as a result of insufficient information regarding their risk status[4].

A final issue concerns the nature of collateral and how it is used by the bank. This issue concerns the measurement problem that arises when collateral is cumulative and not necessarily priced to risk. Collateral is a complex variable when used in empirical regression studies. This complexity has as much to do with the form it takes (binary or continuous) as with its purpose (signalling or priced to risk).

It could be argued that the age of the business and features of the loan contract (interest margin and loan amount) determine whether collateral is taken or not on a loan (binary variable format) to a greater extent than inform the level of collateral taken (continuous variable format). The basis for this argument is that the bank is keen that the business provides collateral in order to signal its commitment to the project. This precondition that is laid down by the bank that the business should provide collateral should be determined by the borrower's risk type. However, the bank cannot use collateral in a very effective way to neutralise the risk of lending because collateral is indivisible and the bank is reluctant to foreclose on the borrower because of the losses that this would entail (Wruck, 1990). Therefore, it is more essential for the borrower to demonstrate his good faith by providing collateral when his risk type necessitates collateral provision. However, the usefulness of

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[3] By 'adverse selection' is meant the phenomenon whereby the bank, by raising the interest rate in order to neutralise risk, attracts riskier borrowers and in so doing raises rather than lowers its risk profile

[4] Furthermore, businesses in industrial sectors where there is a relatively low level of tangible assets to the level of cash flow required are likely to be placed at a disadvantage compared to their counterparts in industries with comparatively heavy concentrations of tangible assets if lending is capital based. This is because if banks favour capital based lending, which a regime of asymmetric information suggests they will because they are unable to adequately assess the viability of a small business's plan, industries lacking in tangible assets will be placed at a disadvantage when applying for bank finance. I could not investigate this question in the context of this chapter due to a lack of appropriate information on firm sector and asset structure.

this collateral as a way of compensating the bank for any subsequent losses is less clear cut. For this reason, I would expect there to be a stronger relationship between the risk type of the firm and the decision to take collateral from the business than for the relationship between the risk type of the business and the level of collateral.

Although this may seem a simplistic argument, anecdotal evidence from interviews with German and Irish bankers from different types of bank suggests that collateral, while an important component of the lending contract, is less important than the viability of the business plan and the credibility of the business principals (Hanley, 1997). The decision to take collateral or not is a function inter alia of the loan purpose where bankers match asset type to collateral type and relegate collateral to second place behind the viability of the business and the business plan. It is natural that bankers would want to portray themselves in the best possible light and therefore understate the significance they attach to collateral and overstate their ability to correctly assess good projects.

I argue that deciding upon a level of collateral as opposed to deciding whether to take collateral or not, cannot be clean cut or scientific. The very indivisible nature of collateral suggests that banks cannot easily match the level of collateral to the level of borrowing. Since a unit of collateral is typically understood to be indivisible, it follows that this unit of collateral must be spread over a number of loans or overdrafts. Real-life data does not typically exhibit neat, clean separations between collateral units. It involves spreading the security over an aggregation of combined borrowing. This feature of collateral being indivisible highlights the need to examine aggregate borrowing rather than loans or overdrafts in isolation. Collateral may furthermore be under- or overvalued and realise less value on disposal than its value as a going concern (sunk cost). Given the comparative 'messiness' of looking at collateral levels rather than the binary decision of whether collateral is taken or not, it might be expected that the same factors driving the decision to take collateral might not be significant in explaining the level of collateral taken.

It is necessary to compare the significance and effects of factors on the level of collateral taken. Firstly, if these factors exert a similar influence on both the binary (decision to take collateral or not) as well as the continuous (level of collateral) response variable, an empiricist can use the decision to take collateral or not as a proxy for the level of collateral taken. Given the difficulty in valuing collateral and assigning its value over individual loans as well as the problem in obtaining estimates of collateral value, using the binary outcome variable of whether collateral is taken or not represents a simplification of the collateralisation process and eases data constraints in this area. This in turn could facilitate further research into the area of signalling and information asymmetry which to date has been hampered by a lack of data.

Because of the influence of collateral to loan ratios in influencing the level of entrepreneurship in the economy and the role of collateral in reducing the problems associated with information asymmetries, collateral is central to any debate relating to the supply of finance to small businesses.

9.3 How my analysis addresses key collateral issues

The aim of this chapter is to examine these collateral issues outlined above by comparing the collateral terms that are granted to new vis a vis existing business borrowers[5].

Particular attention will be paid to research describing how the age of the borrower's account (analogous to the dichotomy between new and existing business borrowers or asymmetric versus symmetric information respectively) influences the level of collateral. Applying the same logic, differences in how collateral levels vary across the two groups correspond to differences arising whereby first time business borrowers have not established an external reputation relative to existing businesses.

I therefore examine the collateral posted by applicants for commercial loans over two adjacent time periods in order to see whether there is a disparity in the way first-period business borrower businesses are treated in terms of collateral requirements viz. a vis existing businesses. The additional constraint of using two time periods acts as a control on the validity of my results.

In comparing the collateral levels provided by new vis a vis existing borrowers, the motivation for this chapter is similar to the motivation behind **Chapter 7** where *entrepreneur-bank* relationships were investigated. Analogous to the investigation of *entrepreneur-bank* relationships in **Chapter 7**, is the dichotomy between how new vis a vis established business customers are treated by a bank in terms of the levels of collateral that they are asked to provide.

9.4 Summary of theoretical work on collateral

Issues concerning the internal reputation of the borrower (existence of entrepreneur-bank relationship on credit terms) were investigated in **Chapter 7**. This chapter deals inter alia with the external reputation of the borrower where more established borrowers are assumed to have higher external reputation effects than less established borrowers. However, there is much overlap between the literature dealing with the internal and external reputations of the borrower. Therefore, much of the theoretical work referred to in **Chapter 2** also applies here. On this basis, I will briefly recall the theoretical work on the predicted effects of reputation on collateral that has already been presented in **Chapter 7** before outlining in more depth the empirical literature.

Arguably the most significant theoretical papers on collateral are by Bester (1985) and Besanko and Thakor (1987b). Both these papers were fully described in **Chapter 2**. Both papers assume an asymmetric information environment where the entrepreneur knows more about his repayment likelihood than the bank. The external reputation of the borrower serves to decrease the level of information asymmetry because the bank or other lender can observe the borrower's survival and infer from this how likely it is that the borrower will repay in the future.

I now relate the level of information asymmetry back to the level to collateral provision. The papers by Bester (1985) and Besanko and Thakor (1987b) assume low levels of external reputation by assuming high level of information asymmetry. Under information asymmetry, borrowers who know they will not default on their repayments to the bank, will provide additional collateral in order to signal their ex ante creditworthiness to the lender.

The only substantial difference between the two papers is the assumption of non-binding wealth constraints by Bester. This leads Bester to conclude that the bank can perfectly distinguish between good and bad borrowers where the good borrowers choose higher collateral levels on their loans, all things equal, than bad borrowers. Because Bester assumes that collateral is subject to <u>non-binding wealth constraints</u>, the amount of collateral extended by entrepreneurs is entirely at their discretion and is not bounded by some upper wealth limit. In other words, entrepreneurs are free to give as much collateral as they like and more cautious, less risky entrepreneurs will give comparatively more collateral than their risky counterparts. On the other hand, because of their assumption of <u>binding wealth constraints</u>, Besanko and Thakor (1987b) argue that the bank cannot perfectly separate good from bad borrowers on the basis of the choice of collateral level because good borrowers do not have an infinite supply of assets to offer as collateral in order to secure their loan.

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[5] Unfortunately, a lack of performance data for existing businesses, prevents me from interpreting my results in the context of whether new businesses are inherently riskier than existing businesses and so justify any possible differentials in collateral levels between the two groups.

The implications of both theoretical papers for any analysis on the effect of external reputation effects on collateral levels are ambiguous. Because both theories offer only explanations of what happens under asymmetric information rather than the lower risk symmetric information environment, there is no prediction as to the relative levels of collateral according as to whether a borrower's information status is symmetric or asymmetric. In other words, I cannot infer whether borrowers whose applications are subject to asymmetric information post more collateral than borrowers whose applications are not subject to this information constraint. What can be concluded however, is that when there is more asymmetric information there may be a wider dispersion of collateral levels (where non-defaulters offer comparatively higher collateral than defaulters) than the dispersion of collateral in the group with less asymmetric information. However, there is no inference from the theories that the average collateral levels in low and high-risk groups or symmetric and asymmetric information regimes respectively should differ. The theories therefore offer little insight on the comparative differences in collateral levels across different information regimes.

9.5 Previous empirical work on collateral

We therefore turn to the empirical literature. There has been empirical work into the decisioning process of whether a bank decides to take collateral or not (Berger and Udell, 1993; Cressy and Toivanen, 2001). Unfortunately there has been no empirical analysis to date of the level of collateral taken. This gap in the literature has meant that while analyses have modelled and demonstrated empirically the decision to take collateral or not, there has been no corresponding empirical analysis that demonstrates whether the same factors affecting the decision to take collateral or not also affect the level of collateral taken.

The analysis by Berger and Udell (1995) models the decision to require collateral from a business as a function of the financial characteristics of the business, its corporate governance, the industry within which it operates and relationship characteristics such as the number of years it has been a bank customer. Their estimations produced the following significant relationships between the explanatory variables and the decision to take collateral[6];

$$\textit{Decision to take collateral} = \alpha + \beta_1\, lev + \beta_2\, arturn + \beta_3\, lnta - \beta_4\, age - \beta_5\, relate + e$$

[6] For the sake of brevity only the variables significant to at least 10 percent are included as explanatory variables here

Where '*lev*' is defined as the ratio between the amount borrowed and total business assets, '*lnta*' is the level of total assets logged, '*arturn*' refers to the turnover of accounts receivable in days, '*lnage*' a relationship variable, refers to the logged number of years the current entrepreneurs have owned the business. This variable '*lnage*' proxies external reputation effects because all lenders can observe it alike. Finally '*lnrelate*', another relationship factor, denotes the logged number of years that the borrower has had a borrowing relationship with the current lender.

The signs on the coefficients of the variables that are significant in their estimations indicate the following relationships. Loans in the form of bank overdrafts are more likely to require collateral when the firm is highly geared and hence the positive sign on '*lev*' (debt forms a higher component of the market capitalisation of the firm). Also positively related to the likelihood that collateral is required, is the level of day's credit granted by the firm to its debtors denoted by a high value for '*arturn*'. This relationship is intuitive because firms that are relatively generous with their credit are in effect granting a loan to their debtors and hence are more likely to stretch their working capital to its limit. Larger firms in terms of total assets are more likely to be required to provide collateral as evidenced by the positive sign for the coefficient of the variable '*lnta*'. The final two variables measuring the reputation of the business are negatively related to the probability that collateral is taken. Therefore more mature entrepreneurs, as denoted by higher values for the variable '*lnage*' and those who have borrowed for a longer period with the bank, as indicated by higher values of '*lnrelate*', are associated with a lower probability that collateral is taken.

Although Berger and Udell find that the likelihood that collateral is taken is negatively associated with the age '*lnage*' variable that proxies external reputation effects, this result is somewhat undermined by their failure to control for loan size in their estimation. Their omission of loan size as a right hand side variable is problematic because we cannot infer that more experienced entrepreneurs are associated with less onerous collateral requirements. If for the sake of argument, more mature firms demand smaller loans (unlikely to be the case as they are likely to be larger firms and hence to have a higher demand for finance) the negative relationship between age '*lnage*' and the likelihood that a loan is collateralised could be influenced by the size of the loan rather than the maturity of the firm. It is safe to assume that the size of a loan is an important variable and its omission runs the risk of model misspecification. What matters more than the amount of collateral required, is the amount of collateral per unit borrowed. If loan size is not controlled for, any results describing the effect of the explanatory variables on collateral level are incomplete.

Cressy and Toivanen (2001) model the hypothesised relationships between their variables before embarking on their empirical analysis. They model the level of collateral '*C*' as;

Level of Collateral C=f(Ind, purp, ***succ****, dur)*

Where '***succ***' (an endogenous variable in the 2-stage least squares estimate) is the ex post risk type of the entrepreneur and indicates whether she defaulted on her loan or not. This should be negatively related with the collateral level if the bank correctly gauges the risk type of the firm at the time that the loan is made. '*purp*' is the loan purpose that represents the purchase of stock, plant, a business, vehicles, improvements to property, working capital and other. It is assumed, although Cressy and Toivanen do not explicitly say so, that if the bank secures a loan on the asset purchased, that categories of the loan purpose variable where an asset was purchased, will be associated with higher levels of collateral. '*Ind*' represents the industrial sector of the business and asset rich sectors should be associated with higher levels of collateral. Finally, '*dur*', the duration of the loan should be associated with higher levels of collateral if longer-term loans. Unfortunately the authors do not have an estimate for the level of collateral, '*C*', in their dataset and use instead a dummy similar to that used by Berger and Udell as a proxy.

Finally, the results of Cressy's (1996a) empirical estimations modelling the decision to take collateral on overdrafts that were offered to UK business start-ups show that the decision to take collateral is a function of the following variables; *'perfin'* indicating whether the business owner invests his own equity in the business project, *'odlim'* the maximum allowable amount of the overdraft, *'marg'* the interest premium and *'pres921'* indicating whether the firm was still in existence at a predefined later period.

9.6 Differences between my analysis and existing work

Unlike the study by Cressy and Toivanen (2001), my analysis does not set out to establish the relationship between the decision to take collateral and the ultimate risk type of the entrepreneur. At a far simpler level, my analysis aims to compare the levels of collateral required from small businesses as a function of whether they are existing or first-period business borrowers. Unlike Cressy and Toivanen who proxy reputation effects using *'lnrelate'*, the logged number of years that a business has banked with the lender, I will proxy reputation using the variable *'type'*. This variable denotes that a firm is a first-period business borrower and hence new borrower where the firm is otherwise an existing and established borrower. It is assumed that the first-period business borrower businesses in my sample are more subject to the limitations of asymmetric information according to

Diamond's theory of the learning bank where a bank learns more about the risk status of its borrower over time (Diamond, 1989; Diamond, 1991) [7]. It would seem intuitive that the bank would impose a higher collateral to loan amount ratio on first-period business borrower firms in order to offset the increased risk of lending to such firms. In other words, for every pound that is loaned, the bank should exact more collateral. The opposite effect would arise, where a bank exacts less collateral from first-period business borrower firms, if start-ups are lacking in assets. In this case the bank is more lenient because it is anxious to win increased market share. Therefore, it is prepared to enter increased risk by increasing its level of unsecured exposure to the small firm in order to prevent a competing bank from claiming this new business customer. It follows that the predicted sign for the type of business customer with respect to the level of collateral is ambiguous.

The analysis by Cressy and Toivanen focuses on ascertaining whether asymmetric information prevails in the market for credit. However, because I do not have a measure for the subsequent performance of the established businesses, I confine the analysis that follows to describing the relationship between the collateral level and the type of business applicant (start-up or established). In so doing, my analysis exhibits two unique features that add to the existing literature. Firstly, I have got two alternative measures of collateral i.e. collateral level and a binary variable indicating whether collateral was taken or not. Neither Berger and Udell (1995) nor Cressy and Toivanen (2001) have explored collateral level, a fact that the latter acknowledge. Indeed, Cressy and Toivanen's exploration of information asymmetries assumes that collateral is continuous (in the modelling part) and yet the empirical part uses a binary collateral variable. They acknowledge this shortcoming in their analysis and note that this replacement of the continuous by a binary variable is necessary due to data constraints. Since no analysis to date has used a continuous measure of collateral, it is useful to explore whether the two variables (binary and continuous) are interchangeable in that the direction of the coefficients explaining collateral as a response variable are invariant with the definition of collateral used. Ultimately, I seek to infer whether the binary decision to take collateral or not represents a useful proxy for the magnitude of collateral since only binary variables have been used in the literature to date.

An additional unique feature of my analysis that differs from previous analyses, is that I control for the collective amount that is borrowed by the entrepreneur. This controlling variable is integral to any analysis of collateral because what should be measured is

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[7] This concept of the learning bank was further developed by Petersen and Rajan (1995) and is explained in **Chapter 2 section 2.46**.

collateral as a proportion of the amount loaned or the amount of collateral extended when the loan amount is kept constant. My analysis is the first therefore, to look at total exposure, which is the amount of collateral securing a given amount of borrowing. It does not make sense to omit the amount borrowed because the higher the amount borrowed, the higher the exposure of the bank to the entrepreneur and hence the greater the need for collateral, all things equal.

9.7 Data description

The data used in this chapter comprises the original dataset of applicants for finance from first-period business borrower or transferred businesses in addition to a further dataset containing applicants who are established customers of the bank i.e. existing customers[8]. The dummy variable *'type'* distinguishes between the two types of borrower.

The breakdown first-period business borrowers and borrowers from established businesses is 1,553 and 2,782 businesses respectively for the first 6 month period in which the bank accepted applications. The number of applicants in my database for the second 6 months is over twice that for the first period with a total of 9,879 businesses. Of these 3,065 were from the first-period business group and the remaining 6,814 from the established business group. The constraint was that all applicants had applied for either a loan or overdraft within either of the 6 month periods. It was possible that applicants who applied within the first 6 months could also apply in the second period and so the two periods do not represent a mutually exclusive set of applicants[9].

The first-period business group, as described before, contains businesses that have transferred their business from another lender or are *ab initio* start-ups. They have been grouped together because neither transfers nor start-ups have a track record with the lender and are hence unknown quantities as far as the lender is concerned. On the other hand, the established business group comprises existing businesses that have a track record with the bank. The variable *'type'* is a dummy variable taking on values of 1 if the loan is to an existing business and zero if not. It follows that the coefficient of the variable *'type'* refers

[8] Unfortunately, there was no way of differentiating between the two types of first-period borrower (businesses that had transferred from another bank and business start-ups) although I was assured by sources at the bank that the number of businesses that had transferred from another bank were very few. The theory would corroborate this. The literature on adverse selection (see **Chapter 2 section 2.2**) confirms that a bank is less likely to accept a business who has previously borrowed from another bank on the grounds that the original lender is unhappy with the borrower's repayment record or risk profile.

to the relationship between membership of the established business group and the response variable, with the first-period business group representing the base category.

The definition of borrowing used in this analysis is aggregate borrowing and is calculated by summing all term loans and overdraft limits applied for and secured during a 6 month time window in 1999. It is necessary to use an aggregate borrowing measure to allow us to use an aggregate collateral measure. This approach is used due to the indivisibilities of collateral. There were anomalies in the collateral data that needed to be addressed prior to working with the data. These anomalies could have arisen as a result of collateral indivisibilities. They first became apparent when I looked through the collateral to loan amount ratios for all borrowers and I initially attributed them to inputting error. Apart from errors made when entering the data, a further reason for excessive collateral ratios is that if collateral has not been decommissioned it remains on the system and does not reflect the current borrowing situation having already served its purpose. Moreover, collateral can be assigned in anticipation of future borrowing in which case it does not reflect the current borrowing situation since it reflects future intentions. Since collateral in the form of real estate is often non-divisible, it is plausible that such anomalies arise. I needed to control for errors arising when collateral data would not be decommissioned but would remain on the system for subsequent loans. The check I performed entailed a modification of my regressions in the next section in order to look at the response variable within acceptable collateral to loan ranges i.e. collateral as a proportion of borrowed amount does not exceed 200 percent. This gives a collateral to loan ratio of 2. This modification is only performed for the response variable when it is continuous. This is because we assume that analyses using dichotomous outcome variables would not have this collateral to loan information on hand since collateral to loan ratios contain collateral level in its continuous variable format in their numerators.

A unique feature of this analysis that is mentioned in **section 9.6** is that it contains both a value for collateral (continuous variable called *'allcoll'*) and a variable indicating whether collateral was taken by the bank to secure borrowing (binary variable called *'yes_no'*). As described in previous chapters the variable *'allcoll'* is calculated by adding the values of land and buildings, guarantees, life policies and cash the owner injects into the project. In all instances, the value of collateral is estimated at its liquidation price by the bank. The percentage mark-down for land and buildings is 30 percent, guarantees is 100 percent and life policies a percentage mark-down that is based on the time to run.

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[9] Because of the proximity of the time periods, it is doubtful that the profile of the applicant type will have changed very much as the population of applicants is likely to have remained stationary (Hanley, 2000).

Keasey and Watson (1996) refer to this mark-down value of collateral as the 'carcass' values arguing that;

'..a relatively illiquid market in second hand plant and equipment would suggest that the value of a business asset for the purposes of collateral is often considered to be much lower than its cost as a new asset'[10] .

As such the dataset allows us to infer whether using dummy variables for collateral influences coefficient signs and significance levels in a way which differs from the conclusions arrived at when using continuous variables. The choice of variables would have repercussions in theory testing exercises where the sign of the collateral coefficient has implications for the information regime that prevails.

I will now outline the hypothesised signs of the main variables in this chapter. In so doing I will refer to their signs in past empirical studies or their hypothesised signs in the theoretical literature.

The next question to ask is which variables influence the bank's decision to take collateral. We know from the review of the literature in **section 9.5** that Berger and Udell (1995) have modelled the collateral level as a function of company size in terms of assets and the duration of the loan. They also included the entrepreneur's age and the business-bank relationship i.e. the number of years that the entrepreneur has been borrowing from the bank, in their regression. Cressy (1996a) models the decision to take collateral on overdrafts as a function of whether the business owner invests his own equity in the business project, the maximum allowable amount of the overdraft, the interest premium and whether the firm was still in existence at a predefined later period. Cressy and Toivanen (2001) model the level of collateral taken by the bank as a function of industrial sector, the purpose of the loan and the duration of the loan as well as the survival status of the firm at a predefined period.

It is evident from the above that the format of the collateral model varies according to the authors, their data limitations and whether the type of loan was something as specific as an overdraft as in the case of Cressy (1996a).

I would summarise the commonalities of the existing models as follows; collateral is a function of the terms of the loan (duration, purpose and amount), the business-bank relationship and some measure of the risk type of the loan (actual ex post survival in both of Cressy's analyses). In addition to the above specification, I would argue for the inclusion of some measure of the assets of the firm that could be used as collateral. For instance, if a loan is secured on a loan applicant's house, then it might be useful to know about the home

[10] Keasey and Watson (1996). P.20

ownership status of the entrepreneur because this indicates whether this asset is available. I would also argue for the inclusion of some measure of past delinquency because this may reflect on the bank's need for additional collateral if the borrower has exhibited risky behaviour in the past. Unlike the Cressy (1996a) model, I do not include the interest margin as an explanatory variable for two reasons. Firstly, I argue that the setting of collateral is independent to the setting of the interest rate because it occurs at an earlier point in time. Hence the application forms for a loan or overdraft do not contain a field for the interest margin because this occurs once the decision to take collateral and grant the loan has taken place. A second reason, is the 'embeddedness' or invariance of interest margins that was discussed in **Chapter 7**. Hence, a loan sanctioner tailors the interest rate to the amount borrowed, level of collateral provided and the type and term of borrowing but has little, if any, discretion over the magnitude of the interest margin[11].

Looking at the variables that I have in my data of existing and first-period borrowers, I match these to the requirements of the model above. Unfortunately, I do not have a measure of the loan duration in my dataset. Loan duration may well be captured under the variable loan purpose (that I do have), where working capital loans are of shorter duration. The categories for the loan purpose variable are as follows; *'assetpu'* indicating that the owner purchased an asset, *'working'*, indicating that the loan was for working capital purposes, *'purchca'* indicating that the owner purchased capital and an *'other'* category which serves as the base category. Whether collateral is taken on a loan or not is expected to be positively related to the loan being used to finance an asset '*assetpu*' and is expected to have a negative sign if the purpose of the loan is to fund working capital, '*working*'. This most liquid type of borrowing does not involve the purchase of tangible assets that could be used to secure the borrowing. It is also to be expected that loans for working capital are less collateralised than loans for business capital according to the golden rule that banks collateralise like assets with like collateral (Hanley, 1997). Optimally highly liquid collateral such as a lien on a deposit account is used to collateralise working capital as it is a highly liquid form of collateral. However, the bank in my sample does not resort to using liens on deposit accounts.

The next loan term used as an explanatory variable is the variable *'total'* indicating the total amount borrowed. I hypothesise that it is positively related to the collateral level or decision to take collateral because as the amount borrowed increases, so also does the exposure of the

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[11] It is interesting that Cressy and Toivanen (2001) do not include interest rate as an explanatory variable in their general model of collateral level but it is included in the Cressy (1996a) paper which investigates the specific case of overdraft finance to start-ups.

bank to the business. There is a need to reduce the risk that accompanies higher exposure by demanding additional collateral.

The next variable which explains the level of collateral taken, or decision to take collateral, is the existence of a business-bank relationship. I represent the business-bank relationship using the variable *'type'* that is coded as 1 if the business is an existing one and 0 if the business is a first-period borrower.

Regarding the expected sign for the coefficient of the business-bank relationship variable *'type'*, I cannot confidently predict the sign of the coefficient *'type'* because arguments for both a positive and for a negative sign can be made (see discussion **section 9.7**). We might expect a negative sign for the following reasons. First, according to the capital gearing approach described by Binks and Ennew (1997), banks use collateral as a way of attenuating the risk on their loans where risk is difficult to gauge ex ante. This was indirectly corroborated by Cressy and Toivanen (2001) who find that collateral increases in ex ante risk. In my sample, the bank has more information about the established business firms than about members of the first-period business group and accordingly we would expect the established business group to offer less collateral. In addition, empirical work by Berger and Udell (1993) found that businesses having longer relationships with a bank and longer business experience, had a lower likelihood of giving collateral. But Berger and Udell did not control for the size of the loan and so when loan size is not controlled for, it appears that businesses with a longer relationship with the bank (the established business group) might exhibit reduced collateral requirements because of reduced information asymmetry.

A positive sign for the coefficient of the variable *'type'* is also possible. If the bank were willing to increase its market share (under perfect competition in the lending market for first period loans because no information monopolies have been established), it might be prepared to accept less than optimal levels of collateral from first-period borrowers. It might be prepared to do so on the basis that first-period business borrowers do not have as many assets to offer as collateral compared to existing businesses. There is empirical evidence for this conjecture. Results from a US study by Hancock and Wilcox (1998) suggests a positive relationship between membership of the established business group and offering collateral. They find that small firms have lower rather than higher collateral to loan ratios due to a shortage of appropriate assets to offer as collateral. Therefore, the coefficient for *'type'*, if coded 1 for established firms, should be positive if a bank is prepared to lower its collateral requirements for asset-poor, first-period borrowers. Furthermore, Hughes (1992) in a UK study finds that smaller companies have a lower ratio of fixed to total assets compared to larger companies (31.5 percent viz. 44.4 percent). They also have comparatively more of their assets tied up in trade debts and other debtors than larger companies (37.9 percent viz. 23.6 percent). The implication of their different asset structure means that they have comparatively fewer assets to offer as collateral to a creditor. So overall, in view of the lack of consensus in the literature, the sign of the '*type*' coefficient cannot be conjectured ex ante because it depends on the leniency of the bank and asset structure of the small business applicant.

The conjectured sign for the coefficient of the variable *'busprem'* is assumed to be positive. This is because *'busprem'* indicates that the entrepreneur owns his own business premises i.e. is a freeholder and hence may have an additional asset to offer the bank as collateral. However, '*busprem*' may be a poor proxy for asset availability, in which case it will be insignificant.

The hypothesised coefficient of the financial difficulty indicator '*debtres*' is positive because I hypothesise that businesses that have exhibited financial difficulty may need to extend additional collateral in order to reduce the bank's exposure to their high risk borrowings (Wruck, 1990).

Several further constraints were placed on the data and these are outlined as follows. My screened dataset contained only borrowers who had borrowed at least £1,000 in either overdraft or term loan form. This was to exclude very small amounts of borrowing that would not necessitate collateral. In a further screening of the data, the ratio of collateral to aggregate borrowing was calculated. If these collateral ratios exceeded 20, as a minority of the observations did, applicants whose collateral ratios exhibited these anomalies were excluded from the dataset. There was a concern that duplication by bank personnel inputting the data had occurred in the right tail of the collateral ratio distribution and a value of 20 represented a generous cut-off point allowing for 'excessive' ratios while excluding the extreme ratios for cautionary reasons.

9.8 Methodology

I specify two different approaches to investigate the relationship between the collateral response variable and the independent variables[12]. The first approach employs a logit specification and the second approach uses a tobit specification.

The first version of the response variable is the dummy '*yes_no*' for collateral. The response variable collateral value is dichotomised into the binary outcomes '*bank takes collateral*'

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[12] See **section 9.2** for discussion on the two types of response variable i.e. binary and continuous

and '*bank does not take collateral*'. This variable '*yes_no*' takes the value of 1 when the bank takes collateral and 0 otherwise. The binary logistic regression model uses the same definition of collateral i.e. the dichotomous outcome variable, as used by Berger and Udell (1995) and by Cressy and Toivanen (2001). It serves as a benchmark against which to compare the outcomes of the subsequent Tobit analysis that uses a continuous variable for collateral.

The format of the binary logit model is;

'*yes_no*' = $\mathbf{Z}_i \beta' + e$

where **Z** is a vector of variables that are summarised in **Table 9.1** along with the expected signs on the coefficients. These variables are further discussed in more detail below.

The analysis moves in a second stage to an estimation of a linear regression using Tobit techniques. While the response variable to be used in the first set of linear regressions is the variable '*yes_no*' as described above, the response variable used in the Tobit analysis is the variable '*allcoll*' which represents the aggregate value of collateral[13].

In order to explore the relationship between collateral level and the explanatory variables that have already been used in the logistic regression, a problem arises. The distribution of the collateral is truncated at 0 because there is no such thing as negative collateral. In order to circumvent this problem, a Tobit specification is used instead of normal OLS. This Tobit uses the latent variable y_i^* which can theoretically take on negative values. But these negative values are not observed, there are none. Thus $y_i^*=0$ due to nonobservability. The format the Tobit takes is;

$-y_i^* = \mathbf{x}_i \beta' + u_i \qquad u_i \sim IN(0,\sigma^2)$

The observed values are related to the latent variable y_i^* as follows;

$y_i = y_i^*$ if $y_i^* \geq 0$

$y_i = 0$ otherwise

The format of the Tobit model is;

'*allcoll*' = $\mathbf{Z}_i \beta' + e$

where **Z** represents the same vector of independent variables as used in the logit model (See **Table 9.1**).

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[13] It is possible to replace collateral level, '*allcoll*', as the dependent variable by the ratio between collateral and aggregate borrowing. However, this alternative approach makes it impossible to isolate the pure relationship between collateral level and the other explanatory variables and is inconsistent with our aim of comparing the effects of the explanatory variables on collateral as the response variable

In the following section, I present the results of the models that are outlined above.

9.9 Results

First of all I present some summary statistics describing the distributions of the data with respect to borrower type before embarking on the regressions that relate the influence of borrower type to collateral level while controlling for other variables.

9.91 Descriptive statistics

The purpose of this section is to shed some light on some distributions within the data in order to generate an idea of the breakdown between the existing business group and the first-period business group across several dimensions.

Figure 9.1 and **Figure 9.2** show the distribution of collateral across the existing business and first-period business groups for borrowing of over £1,000. It can be seen that the first-period business group fares better than the established business group in terms of being less well represented in the fourth quartile representing the highest 25 percent of observations by collateral amount. This counter intuitive result showing that the established business group offer more rather than less collateral, will be examined more closely in the regressions that follow. The pattern whereby the established business group has a comparatively higher presence than its first-period business group counterpart in the fourth quartile holds for the first period (July 1999 until December 1999) and also for the second period (January 2000 until June 2000). The differences seen in these distributions are significant to the 1 percent level as seen in the corresponding cross-tabs (**Table 9.2**).

It can easily be argued that it does not matter if businesses in the established business group appear to have given more collateral because they receive higher loans anyway. In other words, collateral per unit would fall because the established business group are receiving comparatively higher finance than their first-period business borrower counterparts. **Table 9.3** shows that this is not the case. In the first period, only 43.1 percent of the first-period business group were borrowing over the median level compared with 54.5 percent of the established business group. However, by the second period this pattern was reversed with 54 percent of the first-period business group borrowing over the median level compared with 49.1 percent of the established business group.

The lack of an appreciable difference between the two perhaps points to the homogeneity of my sample given that all my firms are small irrespective of their borrowing status. This may explain the blurring of distinction between the established business and first-period business group regarding borrowing amount.

So far we have looked at cross-tabs which describe the difference between borrowers from the established business and first-period business groups in terms of their relative borrowing and collateral levels. However, the issue of borrowing and collateral amount is best expressed as the ratio between collateral and borrowing i.e. collateral to loan value. The question now is whether businesses from the first-period business group are in general more highly geared than their counterparts in the established business group? Since collateral to loan ratios are typically non-normally distributed, they are best logged to give a distribution closer to normality. Altman and Saunders (1998) and Goss et al. (1995) also encountered the same difficulty with non-normally distributed gearing ratios.

I examined the corresponding Q-Q plots to ensure that the logged distributions were indeed more multivariate normally distributed than the untransformed collateral ratios before dichotomising the logged collateral to borrowing ratios around their median for both periods[14].

It can be seen that for the variable *'tot_rat'* comprising the ratio between collateral value and the amount borrowed for the first period of 1999, that the distribution departs from normality (**Figure 9.3**). The observed values describe a curve through the straight line representing the normal distribution. On the other hand, the logged version of *'tot_rat'* denoted by the variable *'ln_tot', shows* an improvement on *'rat_tot'* (**Figure 9.4**).

Since 0 cannot be logged as the result is not computable, I choose to modify the variable *'tot_rat'* before logging it and hence changed zero values to a negligibly small value which approximated 0 . This value could then be logged. The transformed version of *'tot_rat'* i.e. *'ln_tot'* describes a curve on its Q-Q plot that departs less from the straight line indicating the normal distribution. The distribution of the transformed variable *'ln_tot'* is therefore more normal and symmetric than the distribution of the untransformed variable *'tot_rat'* on the basis of the Q-Q plot.

When the relative frequencies of the transformed collateral to loan ratios are compared across the SME borrower type groups, it is suprising that the pattern is inconsistent across the periods (**Table 9.4**). Borrowers from the established business group have a higher

[14] The Q-Q plot method is a procedure of visually checking the distributions being tested against the normal distribution. I compare my distribution of the variable against the normal probability plot. This is obtained by ranking the observed values of a variable from the smallest to the largest and then pairing each value with an expected normal value for a sample of that size from a standard normal distribution. If the distribution of the observations are from a normal distribution, points in the plot should be approximately in a straight line (Norusis, 1990).

likelihood of showing collateral to loan values above the median value in the first period. However, this pattern is reversed in the second period where borrowers from the first-period business group are more likely to exhibit collateral to loan values that are above the median value. I conclude on the basis of this lack of consistency across periods, that differences between my two a priori risk categories are perhaps blurred due to similarity between borrowers in both groups. Rather than comparing small start-ups with large existing businesses, all small business borrowers in my database are small, unquoted companies according to the bank's definition of small. They may represent a more homogenous group of small risky businesses than their different bank relationship status suggests.

It could also be argued that businesses from the established business group may have, by definition, higher assets with which to leverage higher borrowing or signal their creditworthiness. Unfortunately, my dataset does not permit a direct comparison between asset values for both small business groups because the dataset relating to the established business group is limited in the number and scope of its variables. However, I have asset values for a subset of the first-period business group and these are compared against their corresponding level of borrowing. I wish to investigate a link between assets and amount borrowed, although this information pertains to the first-period borrower group alone (**Table 9.5**). It can be seen from **Table 9.5** that higher borrowing is associated with higher levels of assets and that this association is statistically significant. Borrowers from the first-period business group borrowing more than £100,000 are most likely to have at least £175,000 worth of business assets where 69 percent of the highest level borrowers are located in the highest asset category.

9.92 Regression results

I first present and interpret the results from the logit before moving on to the results from the tobits. Looking at the logit for all collateral to loan ranges, businesses from the established business group rather than the busiriesses from the first-period business group are more likely to have provided collateral in both periods. This likelihood is indicated by odds ratios of 1.18 and 1.21 for the first and second periods respectively for the coefficient of the variable *'type'* (*'type'* = 1 for an existing business) (**Table 9.6**).

This suggests that banks may be more lenient on businesses lacking appropriate assets to offer as collateral. This result also seems to corroborate the results of Hancock and Wilcox (1998) where smaller businesses exhibit lower gearing ratios. Those businesses which have been in existence for a while (existing business group) are expected to have accumulated assets which in turn can be used to collateralise loans. This finding of higher collateral requirements for established business group businesses agrees with the summary statistics presented in the '*Descriptive Statistics*' section.

However, the relationship between a higher likelihood of giving collateral and the established business group could be spurious if collateral is not decommissioned after its first use and remains on the data system. Such redundancy would be particularly pronounced for the established business group, which is likely to be already borrowing in periods subsequent to the period in which it commenced its relationship with the bank. There is a higher risk of such redundancy with maturing bank-business relationships not captured in the binary collateral outcome variable.

The variable *'total'* denoting total amount borrowed is significant and positive in both periods, demonstrating that the likelihood of collateral being given is directly related to the amount borrowed.

As expected, the coefficient for the variable *'working'* in both periods is negative. Such loans are not likely to be collateralised because no hard asset is being purchased which could in turn be used to collateralise the working capital loan. A similar reasoning applies to the positive sign on the coefficient for the category of loan purpose implying the purchase of an asset, *'assetpu'*, in both periods. The bank can collateralise the loan using the newly purchased asset as collateral. The coefficient for the category implying the purchase of capital, *'purchca'*, is also positive in both periods.

Although the fact that a business has rescheduled its debts (*'debtres'* = 1) appears to reduce the likelihood of a business providing collateral, this variable is not significant at the 95 percent level for the second period. Finally, the fact that a business operates from its own premises (*'busprem'* = 1) conjectured to be positively related to the likelihood of being collateralised, is not significant for the second period and moves in a different direction in both periods with only the first period the expected positive relationship.

We now move on to the Tobit analysis using the level of collateral as the response variable (**Tables 9.7 and 9.8**). **Table 9.7** shows the results when the dependent variable is the value of collateral. **Table 9.8** shows the results for the same dependent variable when the sample is restricted to only those cases where the collateral to loan ratio was 2 or less[15].

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[15] I initially imposed this restriction of capping collateral ratios at 2 in order to ascertain whether the same relationships applied when collateral to loan value ratios were closer to the 'acceptable range' used by practitioners. Intuitively we know that a banker will not seek a charge over an asset which is worth more than a loan (a collateral to loan ratio in excess of unity). However, owing to the 'carcass' value of collateral described by Keasey and Watson (1996), it is possible that the banker would consider ratios in excess of unity. Notwithstanding this possibility, I would argue that even taking on

The interesting feature of the tobits is the difference in the significance level of the variable *'type'* when controlling for collateral distortions than when these distortions are not controlled for. **Table 9.7** shows that the variable *'type'* is significant: businesses from the established business group are more likely to provide collateral than their counterparts in the first-period business group. However, column 4 of **Table 9.8** shows that *'type'* is no longer significant when collateral to loan value ratios in excess of 2 are excluded and the Tobits rerun. This pattern of non-significance for the variable *'type'* is repeated for both periods when controlling for collateral to loan levels greater than 2.

These disparities between the significance levels of the *'type'* business dummy when controlling for the collateral to loan regime or otherwise, underline the hazard of looking at collateral which has not been decommissioned over subsequent lending periods. When all collateral to loan ranges are investigated in **Table 9.7**, the variable *'type'* is significant in both periods appearing to corroborate the findings of the logits above and supporting the view that the binary variable represents a good proxy for collateral level. However, this is not the case when looking at the level of all collateral, *'allcoll'*, within the arbitrarily 'safe zone' where the collateral to loan ratio reaches a maximum of 2[16]. Here the variable *'type'* becomes redundant and does not obtain any statistical significance in either period 1 or period 2.

This final result cautions against applying collateral data where distortions may exist and demonstrates how these distortions can lead an analyst to make inferences based on spurious relationships. This problem is most likely to arise in comparisons between new borrowers and existing borrowers where the latter group has had time to accumulate collateral over subsequent borrowing periods and hence mismatches between collateral level and borrowing are more likely to occur.

A final test of the validity of collateral level *'allcoll'* under different collateral to loan regimes is performed in column 5 of **Table 9.8**. Column 5 of **Table 9.8** demonstrates that if loan to value ratios in excess of 2 are capped at the threshold value of 2 and the tobits again rerun, that the significance levels of *'type'* increases. On this occasion, it achieves significance in the second period at the 1 percent level but nonetheless fails to be significant for the first period. Therefore, even capping values of collateral suspected to be distorted at

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board the loss in value of an asset on liquidation or resale, collateral to value ratios in excess of two are anomalous (See **section 9.** for a further discussion of why this restriction was made).

[16] I did not use gearing as an explanatory variable because of endogeneity problems. Since its numerator is the same value as the response variable *'allcoll'* and its denominator another explanatory variable *'total'*, we deemed it safer to control for its effects without increasing distortion by including it as an additional explanatory variable

the threshold level is not sufficient to restore the significance level of the business dummy *'type'* in both periods.

However, apart from this disparity between the results when looking at the relationship between business type and collateral level for all collateral to loan levels or a subset of collateral to loan levels, there is less disparity among the other variables. Working capital is consistently negatively related to collateral level as hypothesised while the purchasing of assets is positively related to collateral levels. These results point to the practice of using assets purchased to back lending. Less consistent are the signs and significance levels of the business freeholder and asset proxy variable, *'busprem'*, and the debt rescheduled and proxy for financial distress variable, *'debtres'*. The former is only significant in the first period (all collateral to loan levels) with the hypothesised sign and the latter is not significant in any of the periods or under any of the collateral to loan regimes[17]. The amount of the loan *'total'* is positively related to the level of collateral and is significant in all periods and under all collateral to loan regimes. The results of the tobit in this instance agree with the results obtained in the logit.

The capital purchased dummy, *'purchca'* is both positive and significant for both collateral to loan regimes (second period only). A possible interpretation for its lack of significance in the first period is that business capital is not always useful as an asset and the bank does not use capital such as machinery as collateral. Hence, other more suitable collateral would have to be used.

We now are faced with an ambiguity in interpreting the positive sign of the variable *'type'* with respect to collateral level. On the one hand, it is positive when the loan to value ratio (gearing) is not capped at 2. However, it changes sign when the loan to value ratio is assigned a maximum value of 2. The question is whether we are to conclude from this that the main determinant of the sign of the *'type'* coefficient is poor database management (a spurious outcome arising when collateral is not decommissioned for the established business group) or whether existing firms are really associated with higher collateral levels?

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[17] This inconsistency in the signs and significance levels of *'busprem'* and *'debtres'* is not likely to have been induced by a lack of population stationarity due to the proximity of the two time periods but a lack of robustness in the variables themselves. This lack of robustness could arise for a number of reasons including inappropriate treatment of missing values by data inputters in the case of *'busprem'* or different treatment of borrowers by loan officers for *'debtres'*. Since the relationship between borrower and lender is not controlled for, this latter scenario is likely where leniency towards troubled borrowers differs among loan officers depending on the strength of the individual borrower/business relationship. Troubled borrowers who are 'participative' according to the definition by Binks and Ennew (1997) and cooperate with their banks, may be treated less severely on reschedulement of their loans.

A further check on the validity of my results is to replicate the analysis using a dataset of commercial loans where the spurious outcome (changes in the coefficient of *'type'* with changes in the level of collateral due to redundant collateral left on the system) cannot arise. If we were to look at first-period borrowers only, no collateral would have cumulated on the system that would distort the analysis in the case of the established business group.

In order to perform this cross-validation, I use a different dataset comprising first-period business borrower loans only. I decided to drop the 2-period approach to this analysis in order to simplify the analysis, because this analysis was for cross-validation purposes only and in order to increase the number of observations in the final dataset.

A slight problem arises because I no longer have any *'type'* variable because, by definition, there is no longer any distinction between established business and first-period businesses since we are looking within the first-period business dataset. The first concern is to get a variable to replace the external reputation proxy represented by the variable *'type'* in this cross-validation.

One way of very crudely proxying external reputation effects i.e. the *'type'* variable is to use the internal reputation dummy *'prevbor=1'* that I have used in previous chapters. Although the two variables are not interchangeable, the direction of the two variables with respect to the collateral level variable *'allcoll'* should be the same.

Table **9.9** repeats the tobit analysis using *'prevbor=1'* in lieu of the variable *'type'*. I also replace the asset variable *'busprem'* by the variable *'owned'* because there are fewer missing values for 'owned' in the first-period business borrower dataset and it is roughly equivalent in meaning[18].

The sign of *'prevbor=1'* in the tobit is positive meaning that commercial borrowers who have borrowed in the past are associated with higher collateral levels.

This result is counter intuitive but it corroborates my analysis so far showing that existing borrowers are associated with higher collateral levels. If this is indeed the case, the evidence suggests that banks are lenient with first-time borrowers or first-period business borrowers without a track record by demanding less rather than more collateral. It suggests that collateral is incremental and may be increasing over time. As the borrower becomes more established and enters into successive loan negotiations, the bank increases its level of collateral used to secure its exposure to the business.

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[18] While *'busprem'* means that the owner works out of his own business premises and therefore suggests that he owns a separate business premises, *'owned'* implies that the entrepreneur owns his own premises. It is therefore a better asset proxy than *'busprem'* but unfortunately was not reported for businesses in the established business dataset and so could not be used previously.

The fact that the asset variable indicating that the entrepreneur owns his business premises, *'owned'*, is positively associated with collateral levels also testifies to lenient bank lending practices. Entrepreneurs owing their own business premises are in a position to mortgage them to the bank in return for borrowing. Businesses owing their own premises are also more likely to have higher collateral levels. If their real estate asset is being used to secure borrowing, the conclusion is that available assets are used by the bank as collateral. The corollary to this is that businesses with less real estate (*'owned=0'*) to offer as collateral are associated with lower collateral levels.

It appears therefore from the positive association between *'owned'* and *'allcoll'*, that the bank takes what assets it can as collateral. It may do so on a retrospective basis by claiming comparatively more collateral from non first-period borrowers and the established business group that it claims from first-period borrowers and first-period business borrower businesses.

9.10 Conclusion

The first conclusion of my analysis is that two different specifications i.e. a binary logit and tobit analysis yield similar results when exploring the factors which affect the incidence and level of collateralisation on business loans respectively, but only at a superficial level. The dummy variable *'yes_no'* indicating whether collateral was taken or not and which has been used by all empirical studies so far, performed in much the same way as the response variable denoting value of collateral, *'allcoll'*. However, binary collateral variables lack the incisiveness of collateral level variables because they do not allow the researcher to go beyond the anomalies arising in collateral databases. Given the complexity of collateral data and its possible usage as a goodwill token rather than a scientifically derived price to risk mechanism, sensible analyses of collateral must avoid coming to premature conclusions on the properties of collateral unless prior cognisance is taken of its anomalies. These anomalies would comprise indivisibilities in addition to mismatches between borrowing values and collateral for subsequent periods if collateral were not decommissioned.

There are other problems with using binary collateral variables. Firstly, they confine the econometrics to techniques that deal with binary variables i.e. logits or studies of relative frequencies such as cross-tabs based on the χ^2 distribution. A more important consideration deals with the limited set of conclusions that can be drawn with dichotomous outcome variables. They do not allow the researcher to deal with concepts of more or less but confine the analysis to studies of relative frequencies. The simple *'yes_no'* dichotomy does not permit a differentiation between businesses whose collateral terms are light from those who have had to pay comparatively heavier terms. There is a long continuum of businesses that are charged collateral in varying degrees of magnitude.

However, the main conclusion of my analysis is that there appears to be less disparity in the collateral terms that are extended to first-period business borrowers and existing businesses than thitherto believed. If anything, the evidence points to banks being more lenient to first-period borrowers by taking less collateral, all things equal, than they take from their established business counterparts.

However, this conclusion must remain tentative given that other mechanisms may be at work. For example, the bank may compensate for its level-handedness in the area of collateral by discriminating between businesses in other areas such as interest rates or by rationing credit. The latter hypothesis could not be adequately tested give the lack of assets data for existing businesses which would allow a fuller exploration of the supply dynamics of the lending relationship.

However, we have seen in **Chapter 7** that non first-period borrowers are more likely to be charged higher interest premia on their loans. In **Chapter 8** we saw however, that non first-period business borrowers faced lower rejection rates.

When the evidence in this chapter is evaluated in the context of higher interest margins charged to non-first period borrowers in **Chapter 7**, the overall evidence points to the bank operating as a monopoly lender in periods subsequent to the first lending period. Rather than there being a trade-off between interest rates and collateral, it appears that more established borrowers are being penalised regarding both interest margins and collateral.

The bank is either discriminating against existing businesses because it can get away with it due to high exit costs (Greenbaum et al., 1989). Alternatively, it is being lenient to non-established and first-period business borrowers because it needs to entice these new customers' and first-period lending is a loss-making exercise. Whatever the reason for the bank being more lenient to first-term borrowers in terms of lower interest rates and collateral requirements, the results from this and the previous chapter point unequivocally to a hardening of collateral and interest rates in subsequent borrowing periods.

In order to sum up this chapter I have two main conclusions.

The first is that the dichotomous variable indicating whether collateral was taken or not does not represent an adequate proxy for the level of collateral because it cannot deal with anomalies within the collateral data which could otherwise be attenuated by using appropriate collateral to loan levels.

I also conclude that there is robust evidence when put in context with the results of **Chapter 7** on interest rates, that the bank operates as a monopolist by charging established businesses or established customers higher collateral requirements and interest margins respectively. The corollary to this result that established borrowers are penalised in terms of higher interest margins and collateral requirements, is that the bank charges first-period borrowers lower collateral and lower interest margins than their counterparts who have established a borrowing reputation with the bank. This same result could be interpreted in a more positive light if it emerged that the bank is being more lenient to first-period business borrowers because they are more fragile and are wealth constrained. Due to wealth constraints they demand lower collateral from first-period borrowers.

9.11 Implications of my results for other studies and suggestions for future research

My results suggest that this bank is using its information monopoly over second-period borrowers in order to raise interest rates and increase its level of collateral from the business. In other words, is subsidising its potentially loss-making first-period lending by recouping these costs in subsequent periods. The only way in which the bank could afford to implement this policy without the borrower deserting the lender for the competition, would be in a situation where information monopolies or prohibitive exit costs would prevent the borrower from leaving (Greenbaum et al., 1989).

My results are in line with the predictions of Sharpe (1990) when he argued that businesses are *'informationally captured'*. He argues that even though banks earn zero profits over the life cycle of the average customer relationship, that they are not disciplined by the market in such a way as to make them offer better-performing customers more 'competitive' interest rates. The same reasoning applies to collateral as to interest rates in this context.

'Due to competition....rents are competed away via lower interest rates offered to all firms in their initial period, precisely when banks know least about firms'[19].

Future research should aim to take of board Petersen and Rajan's (1995) study on the level of banking concentration and hence banking competition when conducting studies of this kind. Ideally, future empirical research should indicate the level of banking competition within the lending market where the sample was obtained and interpret the results accordingly. Therefore, while my results appear to apply to a non-competitive banking market where information monopolies can be maintained, it is plausible that other credit markets with fewer information monopolies may be in a position to reward customers in subsequent borrowing periods for their good repayment behaviour. If this were the case, the credit market would exhibit features of Diamond's learning models. If the credit market having perfect information could be described by Diamond's (1989) multiperiod model, a bank could retain a borrower in subsequent periods. The bank could hope to retain the borrower because the borrower expects that the second-period loan terms extended to him would to be more favourable if his first period performance were good (Diamond, 1989; Diamond, 1991). Hence a borrower is rewarded for his good behaviour under perfect competition rather than penalised for it, as we have seen when information monopolies exist.

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[19] Sharpe (1990) Page 1070

A further suggestion for future research would be to obtain data from several countries that are known a priori to have different banking regimes. A researcher could then compare any disparity in the terms that were offered to first-period borrowers and borrowers who are applying for loans in subsequent periods, on a country by country basis.

Not only would a researcher select the countries on the basis of the degree of inter-bank competition and level of small enterprises in the economy. A further possible selection criterion would entail the cost of credit bureau data and level of co-operation among banks regarding the risk status of their customers. With low information costs and in the presence of shared information, information monopolies should not be as pronounced and hence borrowers should have more bargaining power in a multiperiod lending context. This situation would arise because borrowers' reputations would be observable to competing banks. My hypothesis is that with low information costs, and high information availability, the relative cost of borrowing in subsequent lending periods should be lower.

Table 9.1 **List of variables used**

Label	Variable description	Hypothesised sign of coefficient
allcoll	Sum(*land_dv, lpol_dv, guar_dv, non_borr*)	
assetpu	x=1 if asset purchased, 0 otherwise	Positive. The asset is conjectured to be used as collateral until loan redemption
b40_amt	Overdraft amount	
bln_amt	Loan amount	
busprem	x=1 if owner has business premises, 0 otherwise	Positive. The business has additional asset i.e. business premises apart from the family home which can be used as collateral
debtres	x=1 if owner has rescheduled debt, 0 otherwise	
guar_dv	Value of personal guarantees (reduced by markdown)	
land_dv	Value of land and buildings (reduced by markdown)	
lpol_dv	Value of life policy (reduced by markdown if any)	
non_borr	Equity contributed by owner	
purchca	X=1 for capital purchased, 0 otherwise	Positive (as for '*assetpu*')
total	Sum(b40_amt, bln_amt)	Positive. The larger the loan the higher the collateral requirement
type	x=1 for established business group, 0 otherwise	Negative (on balance) - quality of established business group easier to ascertain ex ante (lower risk) and collateral increasing in ex ante risk (Cressy and Toivanen, 1998) - collateral per loan unit i.e. collateral to loan ratio, decreasing in firm size as postulated by the Capital Gearing approach (Binks and Ennew, 1997) + Smaller firms have lower gearing ratios (Hancock & Wilcox, 1998)
working	x=1 for working capital, 0 otherwise	Negative. Loans for working capital should be less collateralised as 'soft' collateral such as liens on accounts and accounts receivable normally used for collateralising working capital is not used by this bank (Hanley, 1997).
yes_no	x=1 for collateral required, 0 otherwise	

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Table 9.2	Collateral by business type			
January-June 1999	*Collateral Quartiles*		TS group	EB group
	1st quartile	*$C \leq 12,050$*	33.4	21.3
	2nd quartile	*$12,050 < C \leq 34,000$*	26.1	22.8
	3rd quartile	*$34,000 < C \leq 80,000$*	22.8	26.5
	4th quartile	*$80,000 < C$*	17.8	29.3
			100	*100*
		value	**df**	**Asymp sig. (2-sided)**
	Pearson chi-square	116.779	3	0.00
July-December 1999	*Collateral Quartiles*		TS group	EB group
	1st quartile	*$C \leq 10,100$*	33.3	35.1
	2nd quartile	*$10,100 < C \leq 30,000$*	19	13.9
	3rd quartile	*$30,000 < C \leq 70,000$*	25.7	24.6
	4th quartile	*$70,000 < C$*	22.1	26.3
			100	*100*
		value	**df**	**Asymp sig. (2-sided)**
	Pearson chi-square	51.947	3	0.00

Table 9.3	Amount borrowed by business type					
	January-June 1999			**July-December 1999**		
	Borrowing ≤ median	*Borrowing > median*	*Tot*	*Borrowing ≤ median*	*Borrowing > median*	*Tot*
TS group	56.9	43.1	*100*	46	54	*100*
EB group	45.5	54.5	*100*	50.9	49.1	*100*
	Value	df	Asymp. Sig. (2-sided)	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	37.793	1	.000	15.198	1	.000

Table 9.4	Logged collateral to loan ratios by business type							
	January-June 1999				**July-December 1999**			
	Logged collateral to loan ratio ≤ median	*Logged collateral to loan ratio > median*		*Tot*	*Logged collateral to loan ratio ≤ median*	*Logged collateral to loan ratio > median*		*Tot*
TS group	53.3	46.7		*100*	43.3	56.7		*100*
EB group	48.3	51.7		*100*	53.6	46.4		*100*
	Value	df	Asymp. Sig. (2-sided)		Value	df	Asymp. Sig. (2-sided)	
Pearson Chi-Square	7.501	1	.006		67.310	1	.000	

Table 9.5	**Amount borrowed by business and assets** (TS group only)				
	Business owned assets	*assets ≤ £60,500*	*£60,501-£175,000*	*assets ≥ £175,001*	*Total*
Amount borrowed	*borrowed ≤ £40,000*	53	22	25	*100*
	£40,001-£100,000	19	61	19	*100*
	borrowed ≥ £100,001	10	21	69	*100*
	value	**df**	**Asymp sig. (2-sided)**		
Pearson chi-square	36.35	4	0.00		

Figure 9.1

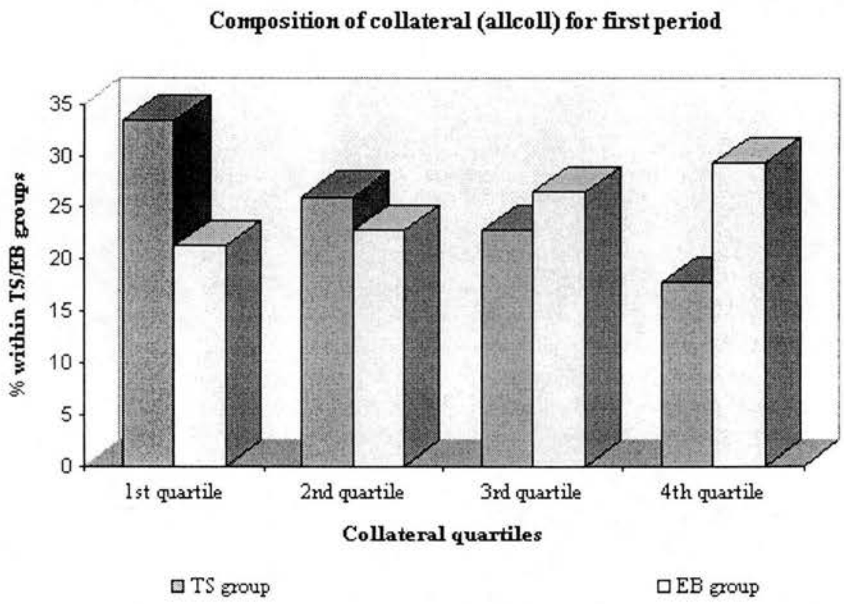

Figure 9.2

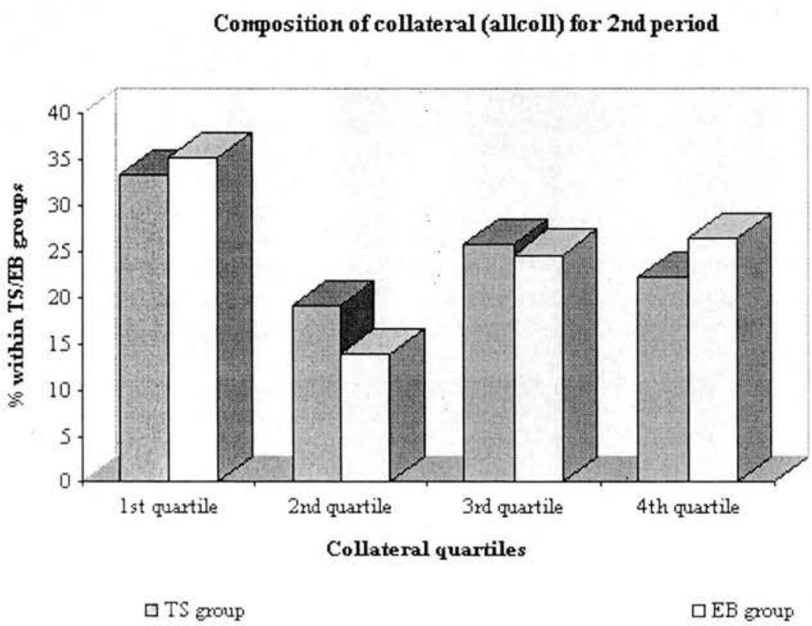

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Figure 9.3 Untransformed ('*tot_rat*') collateral ratio (1st period 1999)

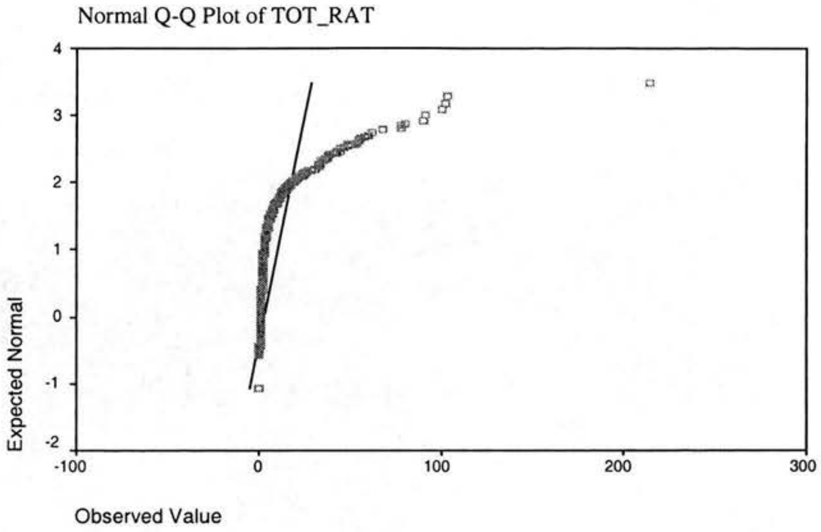

Figure 9.4 Transformed ('*ln_tot*') collateral ratio (1st period 1999)

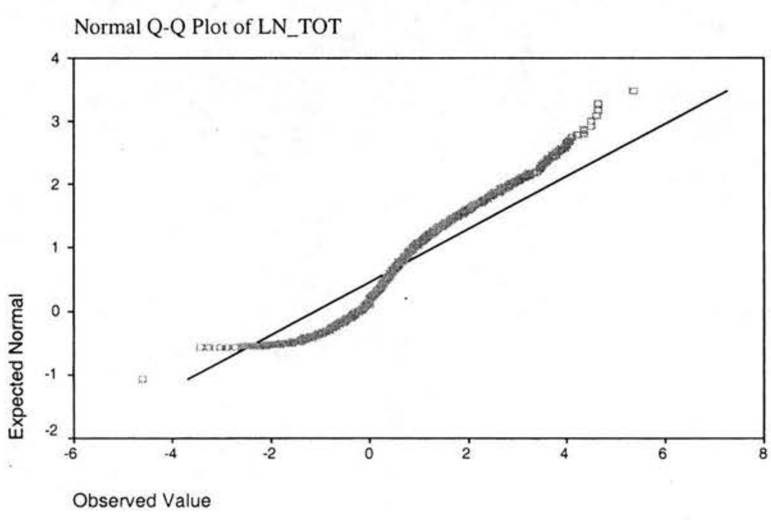

Table 9.6 Variables affecting dichotomous collateral outcome 'yes_no' (borrowing ≥ £1,000)

July 1999 until December 1999						January 2000 until July 2000					
Variable	Std. Estimate (2)	Std. Error (3)	Wald Chi-Square (4)	Pr>Chi-Square (5)	Odds Ratio (6)	Variable	Std. Estimate (2)	Std. Error (3)	Wald Chi-Square (4)	Pr>Chi-Square (5)	Odds Ratio (6)
INTERCPT	.	.19	.00	1.00	.	INTERCPT	.	.13	2.91	.09	.
TOTAL	.24	7.92	49.01	0.00	1.00	TOTAL	.30	5.79	139.71	.00	1.00
TYPE	.04	.09	3.44	0.06	1.18	TYPE	.05	.06	10.17	.00	1.21
ASSETPU	.35	.10	178.01	0.00	3.63	ASSETPU	.38	.07	385.71	.00	4.10
BUSPREM	.05	.16	4.18	0.04	1.40	BUSPREM	.00	.11	.04	.85	.98
WORKING	-.11	.09	21.51	0.00	0.65	WORKING	-.21	.06	141.30	.00	.47
PURCHCA	.10	.19	16.35	0.00	2.17	PURCHCA	.05	.15	11.02	.00	1.64
DEBTRES	-.05	.11	4.82	0.03	0.78	DEBTRES	-.01	.09	.42	.52	.94
		Intercept and co-variates	Chi square for co-variates					Intercept and co-variates	Chi square for co-variates		
- 2 Log L		3592.72	466.642 with 7 DF (p=.0001)			-2 Log L		8883.07	1703.203 with 7 DF (p=.0001)		

Table 9.7

Variables affecting level of collateral *'allcoll'* in period 1 (borrowing ≥ £1,000) (all collateral to loan ranges)					**Variables affecting level of collateral *'allcoll'* in period 2 (borrowing ≥ £1,000)** (all collateral to loan ranges)				
Noncensored values=2738 Left censored values=896					Noncensored values=3457 Left censored values=2797				
Variable	Estimate (2)	Std Err (3)	Chisquare (4)	Pr > Chi (5)	Variable	Estimate (2)	Std Err (3)	Chisquare (4)	Pr > Chi (5)
INTERCEPT	-41283.50	10056.38	16.85	.00	INTERCEPT	-237.17	3021.73	.01	.94
TOTAL	0.86	.03	1093.20	.00	TOTAL	.10	.01	69.16	.00
TYPE	20267.74	4649.37	19.00	.00	TYPE	2907.51	1304.91	4.96	.03
ASSETPU	40229.93	4972.16	65.46	.00	ASSETPU	24402.69	1565.34	243.03	.00
BUSPREM	17768.29	8274.46	4.61	.03	BUSPREM	-229.00	2438.11	.01	.93
WORKING	-15516.80	4960.27	9.79	.00	WORKING	-14148.50	1486.01	90.65	.00
PURCHCA	-1888.44	9458.29	.04	.84	PURCHCA	10089.35	3314.49	9.27	.00
DEBTRES	-8234.13	6507.50	1.60	.21	DEBTRES	2833.88	2197.58	1.66	.20
SCALE	120752.7	1684.303 Normal scale parameter			SCALE	42703.58	562.7266 Normal scale parameter		

Table 9.8

Variables affecting level of collateral *'allcoll'* in period 1 (borrowing ≥ £1,000) (collateral to loan = (allcoll/total)≤2))						**Variables affecting level of collateral *'allcoll'* in period 2 (borrowing ≥ £1,000)** (collateral to loan = (allcoll/total)≤2))					
Noncensored values=1728 Left censored values=896						Noncensored values=2528 Left censored values=2797					
Variable	Estimate (1)	Std Err (2)	Chi-Sqre (3)	Pr>Chi (4)	Pr>Chi All data (5)	Variable	Estimate (1)	Std Err (2)	Chi-Sqre (3)	Pr>Chi (4)	Pr>Chi All data (5)
INTERCPT	-45498.90	7593.63	35.90	.00	.00	INTERCPT	-11717.80	2898.42	16.34	.00	.00
TOTAL	.76	.02	1824.21	.00	.00	TOTAL	.22	.00	2240.05	.00	.00
TYPE	-2959.28	3509.16	.71	.40	.15	TYPE	-838.16	1265.44	.44	.51	.00
ASSETPU	35121.95	3904.69	80.91	.00	.00	ASSETPU	26207.40	1525.04	295.31	.00	.00
BUSPREM	8109.21	6229.41	1.69	.19	.22	BUSPREM	-304.22	2349.70	.02	.90	.65
WORKING	-18185.50	3808.86	22.80	.00	.00	WORKING	-15555.30	1458.54	113.74	.00	.00
PURCHCA	11439.13	7039.55	2.64	.10	.89	PURCHCA	13341.98	3063.79	18.96	.00	.47
DEBTRES	6851.38	4912.72	1.94	.16	.83	DEBTRES	543.95	2128.48	.07	.80	.57
SCALE	76675.91	1352.836 Normal scale parameter				SCALE	37110.97	556.5983 Normal scale parameter			

Table 9.9
Variables affecting '*allcoll*' (TS subset) controlling for asset variable *'owned'*
(all collateral to loan ranges)

Noncensored values=1551 Left censored values 1665					
Variable	DF (1)	Estimate (2)	Std Err (3)	Chisquare (4)	Pr > Chi (5)
INTERCEPT	1	-142701.25	9596.87	221.10	.00
TOTAL	1	0.79	0.03	578.71	.00
PREVBOR	1	50701.92	8599.49	34.76	.00
ASSETPU	1	50398.89	7888.55	40.82	.00
OWNED	1	52830.32	7510.12	49.48	.00
WORKING	1	-6025.85	7276.70	0.69	0.41
PURCHCA	1	1109.42	13728.5	0.01	0.94
DEBTRES	1	49486.88	9037.34	29.98	.00
SCALE	1	171293.976	3301.414 Normal scale parameter		

Chapter 10

Conclusion

10.1 Introduction

This concluding chapter aims to present and interpret all my findings in the context of the wider picture of bank lending to small businesses. Too often the main impact of any findings is lost in the detail of each analysis. The purpose of my concluding chapter therefore is to tie all these main themes together and present the implications of my findings for bank lending policy.

The structure of this chapter is as follows. I first recall the initial aims of my thesis that were laid out in **Chapter 1** and indicate whether they have been addressed. I also supply the findings of my analyses and indicate where they have added to the literature. The section which follows that indicates the policy implications of my findings. A section giving suggestions for future research follows this. Finally, the last section concludes this chapter.

10.2 The aims and findings of my thesis

It helps to recall the aims of my thesis here. I originally set out to construct a scorecard based on the application characteristics of entrepreneurs applying to a major UK retail bank. I also sought to explore some of the financial issues surrounding bank lending to small businesses, in particular, issues relating to the level of collateral, the interest margin and the decision to withhold credit from the borrower.

<u>Addressing the first research question</u>

The first primary aim was to complete a business scorecard based on the borrower's application details. I estimated two main scorecards using the borrowers' application data and two different definitions of default *'Bigdata960E'* and *'Bigdata960F'*.

The most important finding is that the use of application data alone allows a researcher to derive an application scorecard that is better than chance. However, it is likely that the use of credit bureau data would have enhanced these scorecards (Chandler and Johnson, 1992). Unfortunately, the bank did not give me access to credit bureau data. Even without credit bureau data, the scorecards discriminate better than chance between borrowers who do and borrowers who do not default on their repayments.

An additional result of my analysis points to the significance of liquidity in influencing business default. Profit retention and gross profit variables are the most significant variables that influence business default rates. The importance of profitability is borne out in the negative correlation between gross profit and default. Furthermore, there is tentative evidence that the levels of retained profits, if indicative of business growth, reinvestment or liquidity, are positively correlated with default.

Addressing the second research aim

The second research aim was to investigate some of the features of the lending contract namely the interest margin, the decision to withhold credit from the borrower and the level of collateral[1]. What connects the first and second research aims, is that a bank must make the best decision to grant a loan of a certain size and a certain interest rate ex ante i.e. before the creditworthiness of a first-period borrower becomes known. In other words, the bank is making a decision under uncertainty about the borrower's creditworthiness.

Analysis of interest margins

The aim of the analysis into the first of the loan contract terms examined interest margins to see whether the bank acts as a monopolist. A bank can operate as a monopolist if it can retain private information about the borrower's credit status that cannot be seen by competing banks. The aim of this chapter was to investigate the role played by *entrepreneur-bank* relationships in influencing the cost of credit. An *entrepreneur-bank* relationship was defined as a pre-existing relationship, that exists prior to the time in which the entrepreneur applies for his first business loan with the bank.

No existing analysis has yet explored the impact of pre-existing *entrepreneur-bank* relationships on the cost of first-period business borrowing, and so this analysis is unique.

I find that firms with existing *entrepreneur-bank* relationships prior to their application for a loan, pay on average 16 basis points more for their borrowing than through-the-door business applicants. This result may appear counter-intuitive but it agrees with models by Sharpe (1990) and by Greenbaum et al. (1989), that banks offer first-term borrowers lower interest rates than second-period borrowers.

An additional outcome of my analysis is that collateral and interest rates are substitutable. An increase in the value of collateral, causes a reduction in the interest margin. This finding suggests that firms having comparatively higher asset levels may be able to trade off higher collateral levels against a reduction in interest margins.

Similarly, the entrepreneur can expect a reduction on his interest margin for an increase in the amount borrowed. My finding that interest margins are decreasing in the amount borrowed, underpins the conjecture of Petersen and Rajan (1994) that there is evidence of

[1] The reason the three loan contract terms have been examined, for the most part in isolation, is in order to simplify the research but also to follow the precedent set by Stiglitz and Weiss (1981) and Wette (1982) to examine the components of lending separately.

price embeddedness in the volume of borrowing. This suggests that interest margins are transaction-driven.

Analysis of decision to grant credit

The second of the loan contract terms examined was the decision to withhold credit. This analysis deals with the bank's decision to lend or otherwise to a first-period business borrower. I set out to establish which factors affect a bank's decision to reject a request for first-period business finance.

The uniqueness of this analysis is that up to now, only one US analysis has directly investigated the decision to withhold credit (Cole, 1998). This is the first UK analysis of its kind. It is also the first to include human capital variables indicating characteristics of the entrepreneur such as his age.

I find that the loan contract variables and human capital variables are approximately equal in importance to the explanatory power of previous borrowing relationships and credit history and hence are important inputs in the decision process. I also find that entrepreneurs, who have reinvested their earnings in the project or have contributed some of their own equity, are more likely to receive finance than entrepreneurs who do not contribute their own earnings to the business project. Additionally, I find that entrepreneurs who state on their application forms that they see no risks lying ahead, are more likely to receive finance from the bank. Entrepreneurs who can assure the bank that their business can continue to operate even when the owner is sick or absent, are also more likely to receive finance. Finally, entrepreneurs who supply more collateral or request less finance, are less likely to have their application for finance rejected by the bank. This latter result suggests that the bank practices some form of credit rationing. The fact that the bank is more likely to extend finance to existing borrowers rather than 'through-the-door' applicants suggests that the form of credit rationing that the bank practices is likely to be 'transitional' or staggered credit rationing, of the form suggested by Jaffee and Russell (1976).

The results of the analysis dealing with the factors associated with the decision to turn down an application for finance, provides further evidence that underpins the importance of existing *entrepreneur-bank* relationships. The fact that an entrepreneur has previous personal borrowings, is the most important explanation of the decision to turn down a loan application on the basis of its chi-square value. It is more important than the loan contract terms collateral amount and loan amount and more important than the applicant characteristics taken as a group.

This fact bears out what we have already seen in the analysis on interest margins; behavioural information and previous track record are comparable in importance, in informing the interest margin, to any information the bank receives from the borrower on application. The importance of knowledge that a bank can glean from borrowers with a track record cannot be over-emphasised when we consider that an entrepreneur with previous borrowings is 66 percent more likely not have his loan rejected by the bank.

A limitation of the analysis on the credit granting decision

One difficulty arising with this simple analysis, that has not been addressed by either Cole (1998) or Leonard (1992) who both used as their response variable, whether an loan was rejected or not, is that the loan rejection can be initiated by either the bank or the small business. There is therefore an identification problem.

However, the distortion that this would cause is conjectured to be small based on evidence from past research and from conversations with the bank. The Aston Business School (1991) in their discussions with 609 firms, indicates that only 20 entrepreneurs turned down the loans that were offered to them by the bank. These 20 entrepreneurs represent a mere 3.3 percent of the total number of loans that were turned down. Conversations with the bank corroborate this result that very few entrepreneurs turn down loan offers. Perhaps this is the reason why Cole (1998) did not allude to the possibility of identification in his analysis.

Analysis of the level of collateral

This analysis not only investigated the level of collateral provided by entrepreneurs from business start-ups. It also compared collateral levels for new business borrowers with the magnitude of collateral that is provided by existing business borrowers.

This is the first empirical analysis to contrast the collateral levels required from new viz. a vis existing borrowers. A previous analysis has investigated the likelihood that collateral is required from businesses as a function, inter alia, of the business-bank relationship, duration of the loan and size of the firm (Cressy and Toivanen, 2001). Other analyses have compared the likelihood that various types of collateral are required on overdraft finance only (Berger and Udell, 1995; Cressy, 1996a). However up to now, no analysis has directly compared the collateral levels required on bank lending for new vis a vis existing firms respectively.

This is also the first analysis to compare the results obtained using two different definitions of the collateral variable; a binary variable indicating whether collateral was required or not and a continuous variable indicating the level of collateral.

My first finding is that the dichotomous variable indicating whether collateral was taken or not, does not represent an adequate proxy for the level of collateral because it cannot deal with anomalies within the collateral data which could otherwise be attenuated by using appropriate collateral to loan levels.

I also concluded that there is evidence, when put in context with the results of **Chapter 7** on interest rates, that the bank operates as a monopolist by charging established businesses or established customers higher collateral requirements and interest margins respectively. The corollary to this result that established borrowers are penalised in terms of higher interest margins and collateral requirements, is that the bank charges first-period borrowers lower collateral and lower interest margins than their counterparts who have already established a borrowing reputation with the bank.

This same result could be interpreted in a more positive light if it emerged that the bank is being more lenient to first-period business borrowers because they are more fragile and are wealth constrained as suggested by Hughes (1992). Due to wealth constraints banks would demand lower collateral from first-period borrowers.

The overall evidence suggests, that second term borrowing terms are more punitive. If existing borrowers in the collateral analysis are analogous to second-period borrowers in the interest margin analysis, it appears that borrowers from subsequent borrowing periods are charged more for the borrowing in terms of collateral and interest margins than start-up or other new borrowers[2].

My overall evidence suggests that information monopolies exist.

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[2] However, there is another possible interpretation of this result. It is possible that the provision of collateral is of most importance to first period loans and that it diminishes in importance in subsequent periods, as the borrower's creditworthiness becomes known. This possible reduction in the importance of collateral over subsequent borrowing periods, may lead to a failure to update the database. Therefore, an artifact of the data could have driven the result that existing businesses are charged more collateral on their borrowings. This latter qualification means that I cannot provide unequivocal evidence of monopoly bank practice nor of the existence of *'informationally captured'* borrowers. This is because the results could be driven by anomalies within the data where collateral was not decommissioned.

10.3 Policy implications of my thesis

The overall outcome of my customised small business scorecard indicates disappointing classification results on the holdout samples which have direct implications for bank policy. The immediate implications of disappointing scorecard classification results relate to the information regime in which banks operate.

The bank possesses information in the form of application characteristics of the borrower but not enough to permit it correctly classify the bad applicants, without turning down many of the good applicants and hence forfeiting much profit. Unless the cost structure of the bank is such that it can permit such a leakage in the form of turning down potentially good borrowers, a bank is correct in classifying first-period business borrowers as high-risk. With this in mind, the bank could extend a small, introductory loan to the applicant in the first period in the hope that it will discover the creditworthiness of the borrower and that second term borrowing will be less problematic. It therefore does not forfeit the custom of the business and at the same time minimises its exposure to the business.

Although the application characteristics of the borrower do carry weight in influencing the response variable (credit grade), a bank would be better advised to take two alternative options. The first option has been mentioned above i.e. the use of introductory loans to first-period borrowers. The other policy relates to the general small business scoring practice i.e. pooling samples and using generic data.

In Hanley (2000), I have described the practice employed by the Fair Isaac credit scoring company of using pooled data from US retail banks affiliated to the Richard Morris group. In so doing, they have created a substantial dataset of heterogeneous small business borrowers. The larger sample size should help in ensuring that even small correlations between individual explanatory variables such as marital status are detected. With a larger number of observations, there is less chance that these relationships are random but that the relationships are significant.

Of course the implementation of small business scorecards using pooled data, requires a considerable amount of co-ordination among participating banks and perhaps the loss of some competitive advantage since the results are available to all. However, pooled data could be beneficial from a welfare perspective if it took some of the risk out of lending to first term borrowers and therefore was reflected in larger initial loans to start-ups.

Stiglitz and Weiss (1981) point out that using introductory loans or staggered finance, far from decreasing the risk of the small business portfolio, actually increases it. Unlike a credit card user who can scale down his desired spending until it is commensurate with his initial credit card balance, a small business may have to scale down 'discretionary' spending just because it was not given its optimal level of finance. Such spending could include advertising, the holding of inventories or hiring or temporary staff. Such a reduction in finance could have a detrimental effect on a small business at its inception, when it needs the finance most.

Therefore, in order to avoid the adverse consequence of using introductory loans in first-period business lending, private sector initiatives, such as that implemented by Fair-Isaac to pool information among banks, should be encouraged.

There is a further reason underpinning the promotion of pooled information. In my scorecard of first time business borrowers, it was notable that none of the 930 borrowers whose application and performance information was used in the creation of the *'Bigdata930E'* and *'Bigdata930F'* scorecards, had previous accounts with the bank. The question to ask is why did they not apply to take out business loans with the same bank that already ran their private finances? If the original lender had already turned down such entrepreneurs for whom it had behavioural data, such new applications to the bank from which I extracted my data would represent cases of adverse selection. If the banks agreed to exchange information under these circumstances, such possibilities of adverse selection would be reduced.

10.4 Suggestions for future research

Some of my findings have generated scope for future research questions that I have outlined below.

<u>Evolution of a firm's demand for finance over time</u>

There is scope for future research on the basis of my results in **Chapter 7** on the interest margin, to tease out a possible relationship between the evolution of a firm's demand for finance over time as well as the transition from loan to overdraft finance. Given the difficulties that start-up firms experience with overtrading and financing their working capital, it seems anomalous that they would prefer loans to overdrafts. An overdraft is better tailored towards working capital requirements. For this reason, the fact that 'through-the-door' applicants are less likely than firms with *entrepreneur-bank* relationships to receive overdraft finance, may have more to do with supply than demand issues.

Comparative analysis (inter-country) of banking regimes

My results suggest that this bank is using its information monopoly over second-period borrowers in order to raise interest rates and increase its level of collateral from the business. In other words, it is subsidising its potentially loss-making first-period lending by recouping these costs in subsequent periods. The only way in which the bank could afford to implement this policy without the borrower deserting the lender for the competition, would be in a situation where information monopolies or prohibitive exit costs would prevent the borrower from leaving (Greenbaum et al., 1989).

My results are in line with the predictions of Sharpe (1990) when he argued that businesses are *'informationally captured'*. He argues that even though banks earn zero profits over the life cycle of the average customer relationship, that they are not disciplined by the market in such a way as to make them offer better-performing customers more competitive interest rates. The same reasoning applies to collateral as to interest rates, in this context.

Future research should take on board Petersen and Rajan's (1995) study on the level of banking concentration and hence banking competition, when conducting studies of this kind. Ideally, future empirical research should indicate the level of banking competition within the lending market where the sample was obtained, and interpret the results accordingly.

Therefore, while my results appear to apply to a non-competitive banking market where information monopolies can be maintained, it is plausible that other credit markets with fewer information monopolies may be in a position to reward customers in subsequent borrowing periods for their good repayment behaviour. If this were the case, the credit market would exhibit features of Diamond's learning models. If the credit market having perfect information could be described by Diamond's (1989) multiperiod model, then a bank could hope to retain a borrower in subsequent periods. The bank could retain the borrower because the borrower would expect that the second-period loan terms that he would be granted would to be more favourable, if his first period performance were good (Diamond, 1989; Diamond, 1991). Hence a borrower is rewarded for his good behaviour under perfect competition rather than penalised for it, contrary to what we have seen when information monopolies exist.

A further suggestion for future research would be to obtain data from several countries that are known a priori to have different banking regimes. A researcher could then compare any disparity in the terms that were offered to first-period borrowers and borrowers who are applying for loans in subsequent periods, on a country by country basis.

Not only could a researcher select the countries on the basis of the degree of inter-bank competition and the level of small enterprise activity in the economy. A further possible selection criterion could entail the cost of credit bureau data and level of co-operation among banks regarding the risk status of their customers. With low information costs and in the presence of shared information, information monopolies should not be as pronounced and hence borrowers should have more bargaining power in a multiperiod lending context. This situation would arise because borrowers' reputations would be observable to competing banks. My hypothesis is that with low information costs, and high information availability, the relative cost of borrowing in subsequent lending periods should be lower.

10.5 Conclusion

If I were asked to come up with a succinct statement to summarise the findings of my analyses, I would infer from my findings that small businesses are *'informationally captured'*. This inference is based on findings where as the level of information about the borrower increases, so also does the cost to the borrower of his finance in terms of interest margin and collateral.

An additional finding supports my conjecture that information about the borrower is low and possibly asymmetric, in the initial application period. This is due to the relatively poor performance of the business scorecards, where human capital variables alone, such as entrepreneur's age and work experience, are not sufficient to permit a bank make satisfactory judgements about a borrower's quality a priori.

Cressy (1996c) tests the effect of human capital variables but the aim of his analysis is interpretative. My scorecard analysis is rigorous because it represents a more exacting test of the usefulness of human capital variables; are they enough to permit a bank to correctly classify borrowers? My answer to this question is no unless the costs of misclassification of bad risks is as high as that cited by Altman (1977).

There are two possible strategies that a bank can implement to correct these information deficiencies; the bank can offer first-period business borrowers introductory loans (staggered lending) rather than forfeit good business (Type II error). Alternatively, it can attempt to make better application scorecards for first-term borrowers by pooling information with other banks.

Of the two risk reduction strategies, the latter one of pooling information has more to recommend it because it does not lead to the adverse selection and moral hazard effects that the rationing strategy would entail. It would allow the bank to extend the optimal amount of finance to first period borrowers by tapping into information on the track record of the business supplied by a competitor bank.

The obvious drawback of applying this strategy arises if banks wish to maintain their information monopoly. If reciprocal agreements were set up so that there were no free riders, as with the Fair Isaac small business scorecard, the adverse effects of information asymmetries would be reduced, with welfare gains for both small businesses and the bank's shareholders. The welfare gains for small businesses would comprise adequate up-front financing, with possibly higher rejection rates, but more complete financing of those applicants that were successful in obtaining funding. The welfare gains for banks would take the form of lower risk over its small business portfolio. Additionally there would be more consistency and control over the process of loan sanctioning. Furthermore, in the future, the usage of a pooled information system would enhance the automation process for small business loans by leveraging all available information about the borrower that resides in the banking system.

The advantage of having a pooled information system for small business loans and what distinguishes them from larger businesses, is that such an option is feasible for smaller businesses. With larger businesses, the ownership structure is more dispersed and as the information on the individual partners increases exponentially, the value added of a pooled information system is doubtful. With larger businesses the need for pooled information is not an imperative because information is already in the public domain. Pooled information is a potentially useful strategy that could combat the adverse effects of private information and low sample sizes both of which make the appraisal of small businesses problematic.

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Appendix A5

Appendix to Chapter 5

A 5.1 Introduction

This Appendix maps out in detail how I extracted my data at the UK bank and supplements Chapter 5 that provides a summary of the data extraction process.

A 5.2 System of extracting the repayment information

The two years of application data from January 1998 until January 2000 was divided into four periods of approximately six months duration. Application data was available for each of these four periods. The first period was from January 1998 until June 1998. The second extended from June 1998 until December 1998. The third period comprised January 1999 until June 1999. Finally, the fourth period fell between June and December 1999.

The corresponding behavioural information for each of these periods of application data is seen in **Table A 5.1** which outlines data for risk bands where *PER99T6*, *PER99O6*, *PER99O12*, *PER98T6*, *PER98T12*, *PER98T18*, *PER98O6*, *PER9812* and *PER9818* represent the tables containing risk bands once they have been rendered in flat file format. For each of the four time periods, eleven individual tables containing application characteristics are merged with their corresponding performance tables containing risk bands.

In the case of applicants applying in the 1st two periods (between 01-01-98 and 01-12-98), there are theoretically 18 months of behavioural data. However, until January 1999, it was very difficult to match the repayment information of business customers to their original application characteristics due to a flaw in the data capture process. In January 1999, this problem was to some extent addressed whereby branch managers were circulated an advice memo on how to link the two at application. Very many business customers could not be matched with their subsequent repayment performance for the first two periods for this reason.

The risk bands were extracted in the initial stage because the researcher could not undertake the extraction of credit grades and required extraction by authorised banking personnel and it was possible that grades were not available. In the event, grades were available and risk bands were not used in the analysis because they were predicted measures of likely performance rather then observed performance outcomes.

A 5.3 The reformatting of the explanatory variable tables

For all tables that had multiple values of the linking variable for each case, decisions were taking on how to reduce the row entries to one. Each amended table is mentioned below. The reasons for omitting, aggregating or creating new variable categories in order to create a flat table are noted. These justifications are important since certain assumptions are made about the data and constraints set up which will affect the end analysis.

The application characteristics of business borrowers are contained in the following relational databases *TD5APCU*, *TD5APPL*, *TD5BREQ*, *TD5BUP*R, *TD5BURK*, *TD5BUST*, *TD5CUAS*, *TD5CULI*, *TD5FISU*, *TD5OWNR*, *TD5SPOU*, *TD5FISU*, *TD5OWNR*, *TD5SPOU*, *TD5TRPO* and *TD5TRPR* (**Table A 5.2**).

The db2 databases are all linked on the variable *'apcu_id'* corresponding to the customer application number. The extraction of these databases differs depending on whether the relational database is already flat or is categorical. A flat table such as *TD5SPOU* has one unique entry for the linking variable. A categorical table duplicates the values of the linking variable and must be transformed into a flat table. The reason for this repetition is because there may be several different values for variables within the table, causing the link variable to be repeated for this customer.

Since a scorecard takes the unique application characteristics of a business as its explanatory variables, it follows that *'apcu_id'* must be unique if it is to represent a unique row of business characteristics that can be related to the repayment behaviour of the same businesses.

Tables *TD5APCU* to *TD5TRPR* comprise information on the customer. Tables *TD5FACR* to *TD5SECI* refer to information on the application itself. These tables deliver the outcome of the loan application and the pricing of the risk. The risk pricing refers to the terms and conditions extended to the business customer.

What follows is a description of the variables within tables *TD5APCU* to *TD5TRPR* and where changes have been made to variables in order to ensure a unique value for the linking variable *'apcu_id'* in each case.

Application characteristics of customers; tables TD5APCU to TD5TRPR

TD5APCU already has unique values for the link variable *'apcu_id'* and therefore does not need to be reformatted. The table *TD5APCU* lists whether a business has been bankrupted in the past, the structure of the business (legal status), the occupation code of the borrower and the date it commenced trading. It also notes the length of the business to bank relationship, the number of employees and the date it moved to its current address. In addition to these possible explanatory variables of risk, a possible response variable *'risk_rat'* that indicates the risk rating of the business is also included. Variables such as occupation code are not well populated for the first 700 cases. Where observations do occur, they appear to arise in batches (**Table A 5.2**).

TD5APPL is the one table linked by the two major linking variables *'apcu_id'* and *'appl_id'*. Consistent with the need to extract customer application characteristics to estimate the scorecard, the table *TD5APPL* was separated into the tables *TD5APPLC* and *TD5APPLA* depending on whether the link variable was *'apcu_id'* or *'appl_id'* respectively.

There was no need to reformat the table as there were unique entries for the link variable *'apcu_id'*. Variables included the total aggregate customer exposure, the new aggregate exposure, other agreed loan facilities, the borrowing limit on this customer and whether the customer has a credit card facility.

TD5BREQ was a table that needed to be reformatted as there were multiple entries of the link variable *'apcu_id'*. The three general areas requiring restructuring were borrowing purpose, repayment method and reasons cited for taking a higher limit than in former times.

Borrowing purpose that consisted of working capital, purchase of assets, debt rescheduling, the purchase of capital equipment and other reasons was amalgamated into two variables *'purpose1'* and *'purpose2'*. The reason for this restructuring was to do with multi-purpose loans. A loan applicant could check more than one of the five options. In order to capture a second purpose, *purpose2* was defined. Of course theoretically, a customer could check all five options but a variable *'purpose5'* would not be well populated and therefore an attempt was made to note the first two loan purposes. A further justification for this is that this permits conciseness without too much data leakage. Relatively few applicants require a loan with two purposes. Secondly, the categories within purpose are kept as dummies that permit reorganisation into borrowers with certain loan purposes. For example, it may be useful to later on identify borrowers who require finance for rescheduling their loans as these may represent a riskier borrower type. All borrowers showing a '*Re*' value would therefore be separated from those with no '*Re*' value irrespective of whether the rescheduling occurred as *'purpose1'* or *'purpose2'*.

Similarly repayment method was divided into *'repay1'* and *'repay2'* on the assumption that borrowers would rarely have three methods of financing the loan. Some data leakage is inevitable but this is outweighed by the improvement in conciseness and higher population of the data matrix. Borrowers would repay loans based on an anticipated improvement in profitability, on the basis of existing profitability levels or other income at their disposal. The final miscellaneous category was 'other'.

The final transformation of the data was made in the case where borrowers stated their various reasons for requiring a higher limit on the funds they could overdraw (referred to as an overdraft limit). Not all borrowers will request a higher limit and so only a subset of borrowers will have responded to this question. The very fact that they have responded presupposes that they have requested a higher limit and therefore may differ from borrowers who are satisfied with their present limit. This variable could capture growth or alternatively the more negative effects of over-trading. Borrowers could be divided between those who respond to this question and those who do not at a later stage.

The variables '*hi_lm1*' and '*hi_lm2*' were designed to capture the first two reasons cited by the borrower. Again '*hi_lim2*' as expected is not a well-populated field. The reasons for this are twofold. Not all customers request increases of their borrowing limit and secondly not all borrowers will cite more than one justification for the increase in the borrowing limit. The justifications are that the previous expenditure was exceptional, that funds are forthcoming, that the increase in due to seasonal fluctuations, that changes in credit terms were given by the borrower to his customers and that the limit is simply higher. There is also a miscellaneous category.

TD5BUPR is a short table indicating whether the business premises are owned or leased and whether there has been any insolvency in the past. The insolvency variable '*any_inso*' may be collinear with the variable bankrupt from *TD5APCU* since they are measuring much the same thing.

TD5BURK contains details of perceived business risk elicited in the *Business Lending Checklist* does not need to be modified, as there are unique entries for the link variable. The first six variables indicate the types of business risks the business manager perceives himself confronted with. This could be organised into '*risk1*' and '*risk2*' as has been done with *TD5BREQ* as described earlier. The yes/no answers would need to be codified in order to correspond with the categories in question 23 on the *Business Lending Checklist*. The risk categories comprise an increase in local competition '*inc_loca*', implications of new legislation '*legal_im*', a change in the marketplace '*marketpl*', Y2K implications '*adverse_*' and none '*no_risk*'.

The next three variables deal with labour costs followed by three variables measuring the cost of purchases. These could capture the effects of wage bargaining in the case of the wage cost variables and inflation or exchange rates in the case of the cost of purchases variables.

The next six variables measure the changes in the length of creditor and debtor days over a three-year period. These are followed by three variables that measure the perceived change in the cost of finance by the borrower.

Finally two variables estimate the amount of profit or loss retained by the borrower. '*P*' indicates whether it is a profit and '*L*' whether it is a loss.

It should be underlined that *TD5BURK* concerns itself with the borrower's perception of the prevailing economic climate and how it impacts on his business.

TD5BUST deals with business strategy **(Table A 5.2)**. '*Bus_in_l*' indicates whether type of business activity undertaken agrees with its description on the *Business Financial Profile*. '*Prop_val*' indicates whether the business property has been valued in the last 12 months. The level of sales income is denoted by '*sales_in*' and the level of projected sales by '*proj_sal*'. A difference between these two might point to borrower confidence or unrealism. The next variables '*business*' and '*busines0*' indicate cash sales and credit sales in the last 12 months and next 12 months respectively and they are taken from question 28 of the *Business Lending Checklist*. Although the borrower should specify reasons for a change in the former, these reasons are not captured on the database. The ratio between these two has a bearing on the business cashflow. This ratio between cash and credit sales is described by the variables '*rev_inc_split_cash*' and '*rev_inc_split_cred*'. A dummy variable '*sales_pa*' indicates whether all sales income is paid into an account at the bank.

Local_economy_fact ('*local_ec*') indicates whether the lending officer agrees or otherwise with the borrower's prognosis about the risks which the business faces. It indicates the veracity of the borrower's responses to business risks.

Bus_miles_from_br ('*bus_mile*') indicates whether the business is far from its local branch.

Cust_lacks_fin_con ('*cust_lac*') indicates whether in the opinion of the loan officer, the customer seems to lack financial confidence. Like '*local_ec*', this variable reflects the opinion of the loan officer on how competent the borrower is. It is a judgmental variable.

The next five variables cite reasons for a minimum lending margin, if any, and include the usage of a service charge, family connections, a deposit, background assets or other mitigating factors.

Borrowing_purpose (*borrowin*) denotes whether the purpose of the borrowing is in line with the normal activities of the business.

The next three variables '*vat_up_t*', '*ni_paye_*', '*tax_pay_*' indicate whether the VAT, PAYE and taxation payments of the business are up to date.

'*Bus_oper*' notes whether in the opinion of the lending officer, the business can operate without the business principal. It ties in with the concept of business succession.

Finally, '*ins_life*' and '*ins_loan*' capture whether the business owner is covered by life assurance and his loan covered by default insurance.

'*Cust_set*' denotes how often the customer settles VAT where '*Q*' is quarterly, '*M*' is monthly and '*N*' indicates whether the customer is not VAT registered. The latter category could be useful in order to separate out non-VAT registered customers which are predominantly smaller (turnover below £50,000).

TD5CUAS contains a categorisation of assets owned by the customer. The amount if any of a mortgage outstanding against these assets is also noted as well as the value of the assets. This table required extensive reorganisation. It necessitated 83 lines of SAS programming to render it in a flat file format.

The variable *'type'* had categories *'BOA'*, *'SAD'* and *'LP'*. It was assumed that *'BOA'* corresponded to a partially mortgaged or 'bank owned' asset. The basis for making this assumption was that there were positive values for mortgage when the dataset was filtered for *'BOA'* but none when the dataset was filtered for *'SAD'*. *'SAD'* therefore must represent an asset that is solely owned by the business. *LP* represents a Life policy[1].

It follows that any reorganisation of the asset categories must allow for mortgaged values only in the case of BOA category assets. For all other assets, only current values are required.

The values are then summed if unique for each value of the link variable *'apcu_id'*. The reason for this approximation is that if there are multiple rows for one application customer identity e.g. two life policies worth £10,500, the life policies are most likely just repeated. If one of the life policies is worth £5,000 and the second £10,000, there is no duplication and therefore the researcher is safe to sum them across the variable *'apcu_id'* (application customer identity). Although this introduces the possible error that there are in fact two life policies of equal value, the error of double counting duplicate values outweighs this and therefore this policy of aggregation was adopted. This is an instance of where consultation with the bank staff was necessary in order to reformat the data.

TD5CULI describing the customer liabilities, was a table requiring some modification. The amounts outstanding were summed across each customer to yield the aggregate variable *'s_outstd'*. Similarly, monthly repayments and credit limits are summed across *'customer_id'* to yield the summed variables *'s_mrepay'* and *'s_limit'*. *'Timetogo'* is calculated by dividing *'s_outstd'* by *'s_mrepay'*. Excess_limits are denoted by *'ex_lim'*.

TD5FISU contains summary financial variables of the business. This table required some changes to be made. The link variable *'apcu_id'* was repeated for the current and past year's accounting information because accounting information is stored in blocks, the first block relating to the most recent accounting information and the second relating to the accounting information from the year before. Therefore, the extra rows needed to be pulled up and made

[1] Bank personnel themselves were unsure what the variable *'BOA'* implied. Because of this uncertainty, it was not used in my subsequent analysis

into additional columns. Hence, I used the prefix *'pas'* for the past year's value and *'rec'* for the recent year's value. The financial year's beginning *'pas_yrb'* and end *'pas_yre'* are noted. Additional variables were sales turnover *'pas_st'*, gross profit and loss *'pas_gp'*, net profit and loss *'pas_pl'*, pension payments *'pas_pen'*, capital introduced to business during the year in question *'pas_ic'*, trade debtors *'pas_tdr'*, trade creditors *'pas_tcr'* and the total of the capital account. Borrowing costs *'pas_bw'* and past payments *'pas_pay'* are also included in this table.

TD5OWNR, the table describing the business owner, also required modification as there were non-unique entries for the link variable. The problem is that in any one business that is identified by one *'customer_id'*, there can be several business partners. This leads to multiple entries for *'customer_id'*. The solution used here was to take the date of birth of the partner with the largest owner stake to a separate column. This new variable is called *'dob1'*. The years this partner has spent in business are then calculated separately for this partner and termed *'dob1_yi'*. Similarly, the years this partner has spent in this particular type of business are calculated separately and denoted by the variable *'dob1_yt'*.

'Apcu_id' being the linking variable must be made unique with one row per number. The constraint, which was agreed upon was to show entrepreneurs, which have at least 50 percent ownership stakes. This would imply two variables in the case of two partners with equal 50 percent stakes. This constraint should allow small, self-owned businesses to be well represented in the end sample. It would not permit large businesses where ownership is separated from control. This way of organising the data is appropriate for an analysis of small businesses being scored but leads to under representation of the larger players.

For the *TD5OWNR* table below, a SAS programme was written which took the first entrepreneur's date of birth going down the list of linking variables *'apcu_id'* and also the second entrepreneur's data of birth based on share capital ownership. This process was described in **section 5.4.2**.

TD5SPOU deals with information about the entrepreneur's spouse including the spouse's date of birth, occupation, the date his/her employment commenced and spouse's salary. This may be interesting variable when differentiating between cases where the entrepreneur spouse is a partner in the business and when the spouse has an independent source of income. This variable *'spouse's inco*me' has been used in a consumer credit study before (Banasik et al., 1996)[2].

[2] Banasik J.L, J.N. Crook and L.C Thomas. 'Does scoring a subpopulation make a difference?'. The International Review of Retail, Distribution and Consumer Research, April 1996

The final tables *TD5TRPO* and *TD5TRPR* deal with trading creditors and debtors. They were subsumed into one table called *TD5TRADE* due to the interconnectedness of the variables. This table *TD5TRADE* required the most reorganisation in order to render it into a flat file.

In the *Business Lending Checklist* gathering information on the trade creditors and debtors, there are separate fields for debtors and creditors. Information is required from prospective borrowers on the amounts due, from both creditors and debtors. For any debtor and creditor, who are owed or owe amounts of at least 25 percent of the ledger, the amount is listed separately. Lastly, amounts overdue are flagged in a separate field. For all three types of information, both amount and count are requested.

The difficulty with tables *TD5TRPO* and *TD5TRPR* is that the answers to the above straddle both tables and therefore it makes sense to amalgamate both tables into one. This is luckily possible in SAS programming language although the process is involved. 229 lines of code were required to reorganise the tables.

The total sum and count of both debtors and creditors due was calculated. These variables were '*dr_td*', '*dr_tn*', '*cr_td*' and '*cr_tn*' where the suffix '*td*' denoted total due and '*tn*' denoted total number or the count. These variables were already summed as totals and did not therefore require further aggregation.

In the next stage, the large indicator variables were calculated. These were denoted by a '*li*' suffix. All debtors and creditors that exceeded 25 percent of the ledger were counted and the amounts summed. The resulting variables were '*dr_n_li*', '*dr_sm_li*' for the number of large debtors and the summed amounts respectively.

Finally, the amounts overdue were summed to give variables '*dr_sm_od*' and '*cr_sm_od*' and the maximum value outstanding of debtors calculated as '*dr_mx_od*' and '*cr_mx_od*'. It is assumed that a customer is less willing to indicate where he owes large amounts of money to a creditor than to note where amounts are owed to him. Therefore, one would expect few entries for '*cr_mx_od*' compared with '*dr_mx_od*'.

A 5.4 Reformatting of tables TD5FACR and TD5SECI

This section deals with the reformatting of the three most complex tables TD5FACR and TD5SECI. The full list of variables that I extracted is contained in **Table A 5.2**.

I devised a matrix to help me organise the data that is depicted in **Table 5.8**.

These were the most complex tables to render into a flat file format because they were linked at loan application level and not customer application level. A customer may submit several different applications simultaneously. For every application customer identity '*apcu_id*' there could be several different applications each with it's own application identity (*'appl_id'* and *'appl_ver_no'*). An example of this would include an application for a business overdraft at the same time as a term loan.

The first table *TD5FACR* deals with the type of the facility requested. Technically, a loan facility can be fall under one of approximately 90 different account types. A frequency distribution was taken of the dummy variable *'type'* to see which were the most frequently occurring business loans. About 32 percent of loans requested were for business current accounts, 44 percent for business term loans with capital and interest repayments and a further 9.4 percent were for other business term loans. This implied that approximately 14 percent of loan applications fell into other categories. In order to concentrate on the three main types of application, all other loan facilities were assigned to the category of other.

The next issue was to deal with the interest rates. These broke down into about fifty-four groups. The predominant interest rate was the base rate *B* with about 77.6 percent of business owners applying for this. A further 12.9 percent qualified for the *B+* rate while 1.5 percent were eligible for a managed rate *MN*. Finally about 1.1 percent qualified for the flat rate *FL*[3].

Originally the complexity of the data suggested a table like the following to deal with interest rate and facility type relationships in a matrix format whereby the variables are first categorised by interest rate before being further categorised by facility type. Due to very low cell counts for the housing finance (20,21), gold cheque account and the 101 account, these were subsequently assigned to a general other category. Loans not falling into any of the named interest rate types or facility types and hence deemed 'else' or 'other' were aggregated and named as *'other'* category loans. The new compound variable names such as *'b40_int'* for a business current account at base rate are listed in **Table A 5.3** below.

The first attempt at a final dataset involved making 25 separate datasets for both accepted and rejected loans using Table **A 5.3** as a benchmark. Each separate dataset was examined and many datasets had no observations where the interest rates and account types were mutually exclusive. Additionally, it was discovered that the bulk of observations were assigned base (*B*) or base plus (*B+*) interest rates. It was decided to preserve these in as disaggregated form as possible.

However, it was seen on examination of the trial datasets, that customers are not offered both interest rates simultaneously on parts of a loan application. Base rate and base plus rates could therefore be incorporated into the one data column without jeopardising the flat file

[3] The *'MG'* rate was not described in the variable dictionary but this only applied to 3.6 percent of the applicants and so it was eventually included in the *'other'* category.

format. It was also decided to include all base related loans as a separate category given that they were so plentiful. Moreover it was decided to retain the distinction between business current and business loan accounts. All other non-base related accounts were assigned to the category of other account

The suffix *D* stands for the interest dummies (*B*, *B+*, *MN* and *FL*). These were eventually dropped from the final data set as the interest type was could already be identified following separation of the categories by the prefixes of the same. For instance *'B40_int'* would represent a base rate, business current account as signalled by the prefix B.

INT stands for the interest rate for each of these interest dummies and finally *AMT* represents the amount borrowed at each interest rate and for each interest type.

The suffix D stands for the interest dummies (*B*, *B+*, *MN* and *FL*). These were eventually dropped from the final data set as the interest type was could already be identified following separation of the categories by the prefixes of the same. For instance 'b*40_int'* would represent a base rate, business current account as signalled by the prefix B.

INT stands for the interest rate for each of these interest dummies and finally *AMT* represents the amount borrowed at each interest rate and for each interest type.

The flattening of table *TD5FACR* yielded 8 variables, *'current_ac_base_int'*, *'current_ac_base_amt'*, *'current_ac_base_lim'*, *'loan_ac_base_int'*, *'loan_ac_base_lim'*, *'loan_ac_base_amt'*, *'other_ac_interest'* and *'other_ac_amount'*.

TD5SECI represents the table listing the security amounts and values for each borrower. This is also linked by application identity and application version number and hence is similar to *TD5FACR* described above.

The datasheets were put together on a trial and error basis starting from the maximum amount of disaggregation.

As in the case of the table *TD5FACR*, the last versions of the application were taken. Next a frequency table was produced for each security type and it was concluded that land (*'land'*), life policies (*'lpol'*) and guarantees (*'guar'*) comprised the list of most frequently used security. Altogether, these three security types accounted for 92.9 percent of all security taken. Land was taken in 48.4 percent of cases, life policies in 36.7 percent and guarantees in 7.8 percent of cases between 01-01-1999 and 01-06-1999.

The original security type dummy was divided into *'land'*, *'lpol'* and *'guar'* with an *'other'* category for any security not fitting into these categories. The linking variable *'apcu_id'* was then integrated into the dataset as this was needed in order to aggregate security by customer application identity. It would not have been possible to aggregate security by the existing link variables *'appl_id'* and *'appl_ver'* as these were at application level. The percentage variable discount percent value as indicated by the suffix '*DP*' was not summed but rather averaged over values of the link variable '*apcu_id*'. The variables discount value, indicated by the suffix '*DV*' and value indicated by '*V*' were summed across '*apcu_id*'.

This process of aggregation was carried out separately for security in the land, life policy, guarantee and other categories before the resulting temporary data sets were merged.

15 new variables were calculated. '*Land_val*', '*land_dp*', '*land_dv*' and '*land_ef*' stand for the following. '*Land_val*' represents the book value of land used as collateral. '*Land_dp*' the discount percent that this book value would be devalued by in the event of the asset being liquidated. '*Land_dv*' indicates the value of this discount mark down. '*Land_ef*' denotes whether the land had been used to cover existing facilities. The latter dummy variable would not play a part in the case of start-up and transfer businesses because they would not have existing facilities to begin with since this is assumed to be their first application.

The same variables describe the value and discount values for the other collateral types life policies and guarantees.

Table A 5.1 Application scorecard variables and connection risk bands

Application variables		Connection risk bands		
Estimation period	***Source tables*** (for explanatory variables)	***6 mths later***	***12 mths later***	***18 mths later***
01-06-99 until 01-12-00 **1999 2nd period**	**Sanfaci** **Applc** **Breq** **Bupr** **Bust** **Cuas** **Culi** **Fisu** **Ownr** **Seci** **burk**	01-07-00 Dataset: **PER99T6**		
01-01-99 until 01-06-99 **1999 1st period**	**sanfaci** **applc** **breq** **bupr** **bust** **cuas** **culi** **fisu** **ownr** **seci** **burk**	15-01-00 Dataset: **PER99O6**	15-07-00 Dataset: **PER99O12**	
01-06-98 until 01-12-98 **1998 2nd period**	**Sanfaci1** **Applc1** **Breq1** **Bupr1** **Bust1** **Cuas1** **Culi1** **Fisu1** **Ownr1** **Seci1** **Burk1**	01-07-99 Dataset: **PER98T6**	15-01-00 Dataset: **PER98T12**	15-07-00 Dataset: **PER98T18**
01-01-98 until 01-06-98 **1998 1st period**	**Sanfaci2** **Applc2** **Breq2** **Bupr2** **Bust2** **Cuas2** **Culi2** **Fisu2** **Ownr2** **Seci2** **Burk2**	15-01-99 Dataset; **PER98O6**	15-07-99 Dataset; **PER9812**	15-01-00 Dataset; **PER9818**

Table A 5.2 Eventual variables used in final dataset

DB2 TABLE	VARIABLE LABEL	NOTES
TD5APCU_APP_CUST	Bankrupt_or_seques *(bankrupt)* Business_structure *(business)* Borrowing_since *(borrowin)* Occupation_code *(occupati)* Date_strt_trading *(legal_st)* Risk_rating *(date_str)* Length_of_connect *(number_o)* Act_no_employees *(franchis)* Date_moved_to_addr *(risk_rat)*	
TD5APPL_APPLICATN (TD5APPLC)	Total_agg_exposure *(total_ag)* Contingent_liabilities *(continge)* RBS_CC_facilities *(rbs_cc_f)* BACS_limit *(bacs_lim)* Total_amount_borr *(total_am)* New_aggregate_borrowing *(new_aggr)* Decision_type *(decision)* Other_agreed_facilities *(other_ag)* Low_risk_proc_qual *(low_risk)*	
TD5BREQ_BORR_REQT	First_loan_purpose *(purpose1)* Second_loan_purpose *(purpose2)* First_repayment_method *(repay1)* Second_repayment_method *(repay2)* First_reason_for_higher_limit *(hi_lm1)* Second_reason_for_higher_limit *(hi_lm2)* Borrowed_amount *(borrowed)* Non-borrowed_amount *(non_borr)* Business_premises_size *(bus_prem)* Cust_replace_business_assets *(cust_rep)*	Loan purpose has values; WC = working capital AS = Assets Re = refinancing Ca = capital equipment Repayment method has values; P = profitability improve E = existing profitability levels I = Other income O = Other Reason for higher limit has values; Except = previous expenditure exceptional Funds = Exceptional receipt of funds expected Season = seasonal fluctuations Credit = Change in credit given H_L = this is a higher limit Other = other reason
TD5BUPR_BUSPROFILE	Leased_or_owned *(leased_o)* Any_insolvency *(any_inso)*	

Table A 5.2 Ctd.

DB2 TABLE	VARIABLE LABEL	NOTES
TD5BURK_BUS_RISK	Inc_local_competn (y/n) *(inc_loca)* Legal_implications (y/n) *(legal_im)* Marketplace_resizi (y/n) *(marketpl)* Adverse_comp_proj (y/n) *(adverse_)* No_risk (y/n) *(no_risk)* Other_risk (y/n) *(other_ri)* Lab_cost_last_12m *(lab_cost)* Lab_cost_next_12m *(lab_cos0)* Lab_cost_NA (y/n) *(lab_cos1)* Cost_pur_last12m (cost_pur) Cost_purch_next_12m *(cost_pu2)* Cost_purch_na (y/n) *(cost_pu3)* Cred_days_last_12m *(cred_day)* Cred_days_next_12m *(cred_da4)* Creditor_days_na (y/n) *(creditor)* Debt_days_last_12m *(debt_day)* Debt_days_next_12m *(debt_dA 5)* Debtor_days_NA (y/n) *(debtor_d)* Fin_cost_last_12m *(fin_cost)* Fin_cost_next_12m *(fin_cos6)* Finance_costs_na *(finance_)* Retained_prof_loss (amount) *(retained)* Retain_prof_or_los (y/n) *(retain_p)*	

Table A 5.2 Ctd.

DB2 TABLE	VARIABLE LABEL	NOTES
TD5BUST_BUS_STRAT	Bus_in_line_BFP *(bus_in_l)* Prop_val_last_12m *(prop_val)* Sales_inc_last_12m *(sales_in)* Proj_sales_next_12m *(proj_sal)* Business_inc_cash *(business)* Business_inc_cred *(busines0)* Rev_inc_split_cash *(rev_inc_)* Rev_inc_split_cred *(rev_inc1)* Sales_paid_to_RBS *(sales_pa)* Local_economy_fact *(local_ec)* Bus_miles_from_br *(bus_mile)* Cust_lacks_fin_con *(cust_lac)* Mlm_service_charge *(mlm_serv)* Mlm_family_connect *(mlm_fami)* Mlm_deposits *(mlm_depo)* Mlm_bg_assets *(mlm_bg_a)* Mlm_other *(mlm_othe)* Borrowing_purpose *(borrowin)* VAT_up_to_date *(vat_up_t)* NI_PAYE_up_to_date *(ni_paye_)* TAX_pay_up_to_date *(tay_pay_)* Bus_operate_withou *(bus_oper)* Sickness_disabilit *(sickness)* Ins_life_cover *(ins_life)* Ins_loan_guard *(ins_loan)* Cust_settle_of_VAT *(cust_set)*	
T D5CUAS_CUST_ASSET	Sum_BOA_presentvalu *(s_boapv)* Sum_SAD_presentvalu *(s_sadpv)* Sum_BOA_amount *(s_boamt)*	I think that BOA is acronym for business owned assets but bank sources were unable to confirm. From Business Financial Profile. SAD from *Personal Financial Profile*
TD5CULI	Sum_of_amounts_outstanding*(S_outstd)* Sum_of_monthly_repayments*(S_mrepay)* Sum_of_credit_limits*(S_limit)* Sum_of_amounts_outstanding/ Sum_of_monthly repayments*(Timetogo)* Excess limit = Sum_of_credit_limits – Sum_of_amounts_outstanding *(Ex_lim)*	

Table A 5.2 Ctd.

DB2 TABLE	VARIABLE LABEL	NOTES
TD5FACR_FACLTY_REQ **(linked with Appl_id)**	Appl_id (*fk_appl_*) Fk_appl_ver_no (*Fk_appl0*) Prop_int_type (*prop_int*) Prop_int_ratea (*prop_in1*) Proposed_limit (*Proposed*) Agreed_lim_pre_app (*agreed_l*) Fk_faty_code (*fk_faty_*)	Prop_int_type (*prop_int*); B 81.4% B+ 7.8% MN 5.4% D 3.1% F 0.2% FL 0.9% M 0.9% MG 1.1% Fk_faty_code (*FK_FATY_*) 01 2.9% 08 3.6% 10 0.7% 101 1.4% 105 2.9% 12 2.6% 20 0.9% 21 1.7% 40 41.7% 50 5.3% 51 35% 52 1.4%

Table A 5.2 Ctd.

DB2 TABLE	VARIABLE LABEL	NOTES
TD5FISU_FINCL_SUM	***Past year*** Past_fin_yr_begin *(pas_yrb)* Past_fin_yr_end *(pas_yre)* Past_sales_turnover *(past_st)* Past_yr_gross_prof *(pas_gp)* Past_yr_pl *(past_pl)* Past_bus_drawings *(pas_bd)* Past_net_prof *(pas_np)* Past_pension_pay *(pas_pen)* Past_increase_cap *(pas_ic)* Past_retained_profi *(pas_rp)* Past_debtors *(pas_tdr)* Past_creditors *(pas_tcr)* Tot_acc_or_nta_net Past_borrowing_costs *(pas_bw)* Past_payments *(pas_pay)* ***Recent year*** Present_fin_yr_begin *(rec_yrb)* Present_fin_yr_end *(rec_yre)* Present_sales_turnover *(rec_st)* Present_yr_gross_prof *(rec_gp)* Present_yr_pl *(rec_pl)* Present_bus_drawings *(rec_bd)* Present_net_prof *(rec_np)* Present_pension_pay *(rec_pen)* Present_increase_cap *(rec_ic)* Present_retained_profi *(rec_rp)* Present_debtors *(rec_tdr)* Present_creditors *(rec_tcr)* Tot_acc_or_nta_net Present_borrowing_costs *(rec_bw)* Present_payments *(rec_pay)*	
TD5OWNR	Percent_ownership_ptnr1 **Partner1** Date_of_birth Years_in_business Years_in_type_of_business **Partner2** Date_of_birth Years_in_business Years_in_type_of_business	

Table A 5.2 Ctd.

DB2 TABLE	VARIABLE LABEL	NOTES
TD5SECI_APP_SEC_ITM **(linked with Appl_id)**	Appl_id (*fk_appl_*) Fk_appl_ver_no (*fk_appl0*) Security_type (*security*) Status (*status*) Secures_house_purc (*secures_*) Valuation_amount (*valuatio*) Discount_percent (*discount*) Discount_value (*discoun1*) Exist_facilit_sec (*exist_fa*)	Security_type: B&FC 1.6% DEB 1.2% GUAR 2.8% LAND 32.7% LOFP 0.6% LPOL 58.6% OTH 2.2% SCRP 0.3% Status: HLD, INC, OFD Secures; Y/N
TD5SPOU_SPOUSE	Date_of_birth Occupation Start_with_emp_dat Annual_salary	
TD5TRPO TD5TRPR_TRAD_PRNR	Tot_sum_drs_due (*dr_td*) tot_n_drs_due *(dr_tn)* tot_sum_crs_due *(cr_td)* tot_n_crs *(cr_tn)* lrgindicator_n_drs *(dr_n_li)* lrgindicator_sum_dr *(dr_sm_li)* lrgindicator_max_dr *(dr_mx_li)* lrgindicator_n_crs *(cr_n_li)* overduedue_sum_drs *(dr_sm_od)* overdue_sum_crs *(cr_sm_od)* overdue_max_dr *(dr_mx_od)* overdue_max_cr *(cr_mx_od)*	

Table A 5.3 **Template for reformatting TD5FACR**

	B						
	Business current a/c	**Term loan (capital & interest)**	**Term loan**	**house(20,21)**	**Gold cheque a/c**	**101 a/c**	**other**
interest dummy	B40_D	B51_D	B50_D	Bhse_D	B1_D	B101_D	
interest rate	B40_INT	B51_INT	B50_INT	Bhse_INT	B1_INT	B101_INT	
amount	B40_AMT	B51_AMT	B50_AMT	Bhse_AMT	B1_AMT	B101_AMT	
	B+						
	40	**51**	**50**	**house(20,21)**	**1**	**101**	**other**
interest dummy	B+40_D	B+51_D	B+50_D	B+hse_D	B+1_D	B+101_D	
interest rate	B+40_INT	B+51_INT	B+50_INT	B+hse_INT	B+1_INT	B+101_INT	
amount	B+40_AMT	B+51_AMT	B+50_AMT	B+hse_AMT	B+1_AMT	B+101_AMT	
	MN						
	40	**51**	**50**	**house(20,21)**	**1**	**101**	**other**
interest dummy	MN40_D	MN51_D	MN50_D	MNhse_D	MN1_D	MN101_D	
interest rate	MN40_INT	MN51_INT	MN50_INT	MNhse_INT	MN1_INT	MN101_INT	
amount	MN40_AMT	MN51_AMT	MN50_AMT	MNhse_AMT	MN1_AMT	MN101_AMT	
	FL						
	40	**51**	**50**	**house(20,21)**	**1**	**101**	**other**
interest dummy	FL40_D	FL51_D	FL50_D	FLhse_D	FL1_D	FL101_D	
interest rate	FL40_INT	FL51_INT	FL50_INT	FLhse_INT	FL1_INT	FL101_INT	
amount	FL40_AMT	FL51_AMT	FL50_AMT	FLhse_AMT	FL1_AMT	FL101_AMT	
	Else						
	40	**51**	**50**	**house(20,21)**	**1**	**101**	**other**
interest dummy							
interest rate							
amount							

Appendix 5.1 Personal Financial Profile

Host table	Variable name	Type	Length	Location on *Personal Financial Profile*
TD5APCU	POSTCODE	CHAR	8	C10
TD5APCU	OCCUPATION_CODE	CHAR	2	C10
TD5APCU	OCCUPATION_DESC	CHAR	30	C10
TD5SPOU	EMPLOYER	CHAR	25	C10
TD5SPOU	OCCUPATION	CHAR	30	C10
TD5SPOU	ANNUAL_SALARY	INTEGER	4	C11
TD5SPOU	START_WITH_EMP_DAT	DATE	4	C12
TD5APCU	DATE_OF_BIRTH	DATE	4	C5
TD5CUAS	EST_PRESENT_VALUE	INTEGER	4	C59
TD5CUAS	MORTGAGE_OUTSTAND	INTEGER	4	C60
TD5CUAS	OWNED_SOLE_OR_JOIN	CHAR	1	C61
TD5CUAS	PROPERTY_LET	CHAR	1	C62
TD5APCU	NO_OF_DEPENDENTS	SMALLINT	2	C7
TD5CUAS	CASH_DEPOSIT_BANK	CHAR	30	C71
TD5CUAS	LIFE_POLICY_DEATH	INTEGER	4	C73
TD5CUAS	ASSET_DESCRIPTION	CHAR	30	C74
TD5APCU	MARITAL_STATUS	CHAR	15	C8
TD5APCU	HOME_OWNER_IND	CHAR	1	C9

Appendix 5.2 Business financial profile

Host table	Variable name	Type	Length	Location on *Personal Financial Profile*
TD5APCU_APP_CUST	DATE_STRT_TRADING	DATE	4	D2
TD5APCU_APP_CUST	DATE_MOVED_TO_ADDR	DATE	4	D3
TD5APCU_APP_CUST	NATURE_OF_BUSINESS	CHAR	1	D6
TD5APCU_APP_CUST	NUMBER_OF_EMPLOYEE	CHAR	1	D7

Appendix 5.3 Business Lending Checklist Variables

Host table	Variable name	Type	Length	Location on *Personal Financial Profile*
TD5APCU	BANKRUPT_OR_SEQUES	CHAR	1	B1
TD5CRSE	BANKRUPT_OR_SEQUES	CHAR	1	B1
TD5BREQ	REPAY_PROF_IMPROVE	CHAR	1	B100
TD5BREQ	REPAY_OTHER_METHOD	CHAR	1	B101
TD5BREQ	BUS_PREMISES_SIZE	CHAR	1	B102
TD5BREQ	CUST_REPLACE_BUS	CHAR	1	B113
TD5BREQ	CUSTOMER_VALUATION	CHAR	1	B126
TD5FACR	PROPOSED_LIMIT	INTEGER	4	B131
TD5BREQ	SEASONAL	CHAR	1	B132
TD5BREQ	CHNG_IN_CRED_GIVEN	CHAR	1	B132
TD5BREQ	HIGHER_LIMIT	CHAR	1	B132
TD5BREQ	LIM_SUFF_OTHER	CHAR	1	B132
TD5FACR	AGREED_LIM_PRE_APP	INTEGER	4	B132?
TD5BREQ	DELAY_IN_MONIES_GI	CHAR	1	B133
TD5BREQ	MAX_BORROW_MONTHS	CHAR	15	B134
TD5BREQ	MAX_NEW_BORROWING	INTEGER	4	B135
TD5BREQ	NAME_INCOME_M0NTH1	CHAR	3	B136
TD5BREQ	INC_MONTH_1_NEXT	INTEGER	4	B137
TD5BREQ	INC_MONTH_2_NEXT	INTEGER	4	B138
TD5BREQ	INC_MONTH_3_NEXT	INTEGER	4	B139
TD5BREQ	INC_MONTH_4_NEXT	INTEGER	4	B140
TD5BREQ	INC_MONTH_5_NEXT	INTEGER	4	B141
TD5BREQ	INC_MONTH_6_NEXT	INTEGER	4	B142
TD5BREQ	INC_MONTH_7_NEXT	INTEGER	4	B143
TD5BREQ	INC_MONTH_8_NEXT	INTEGER	4	B144
TD5BREQ	INC_MONTH_9_NEXT	INTEGER	4	B145
TD5BREQ	INC_MONTH_10_NEXT	INTEGER	4	B146
TD5BREQ	INC_MONTH_11_NEXT	INTEGER	4	B147
TD5BREQ	INC_MONTH_12_NEXT	INTEGER	4	B148
TD5BREQ	INC_MONTH_1_PAST	INTEGER	4	B149
TD5BREQ	INC_MONTH_2_PAST	INTEGER	4	B150
TD5BREQ	INC_MONTH_3_PAST	INTEGER	4	B151
TD5BREQ	INC_MONTH_4_PAST	INTEGER	4	B152
TD5BREQ	INC_MONTH_5_PAST	INTEGER	4	B153
TD5BREQ	INC_MONTH_6_PAST	INTEGER	4	B154
TD5BREQ	INC_MONTH_7_PAST	INTEGER	4	B155
TD5BREQ	INC_MONTH_8_PAST	INTEGER	4	B156
TD5BREQ	INC_MONTH_9_PAST	INTEGER	4	B157
TD5BREQ	INC_MONTH_10_PAST	INTEGER	4	B158
TD5BREQ	INC_MONTH_11_PAST	INTEGER	4	B159
TD5BREQ	INC_MONTH_12_PAST	INTEGER	4	B160
TD5BURK	CUST_BIGGEST_OPPOR	VARCHAR	100	B162
TD5BURK	INC_LOCAL_COMPETN	CHAR	1	B163

Appendix 5.3 Business Lending Checklist Variables (Ctd.)

Host table	Variable name	Type	Length	Location on *Personal Financial Profile*
TD5BURK	LEGAL_IMPLICATIONS	CHAR	1	B163
TD5BURK	MARKETPLACE_RESIZI	CHAR	1	B163
TD5BURK	ADVERSE_COMP_PROJ	CHAR	1	B163
TD5BURK	NO_RISK	CHAR	1	B163
TD5BURK	OTHER_RISK	CHAR	1	B163
TD5BURK	LAB_COST_LAST_12M	DECIMAL	10	B164
TD5BURK	LAB_COST_NEXT_12M	DECIMAL	10	B165
TD5BURK	LAB_COST_NA	CHAR	1	B165
TD5BURK	COST_PURCH_LAST12M	DECIMAL	10	B166
TD5BURK	COST_PURCH_NEXT12M	DECIMAL	10	B167
TD5BURK	COST_PURCH_NA	CHAR	1	B167
TD5BURK	CRED_DAYS_LAST_12M	SMALLINT	2	B170
TD5BURK	CRED_DAYS_NEXT_12M	SMALLINT	2	B171
TD5BURK	CREDITOR_DAYS_NA	CHAR	1	B171
TD5BURK	DEBT_DAYS_LAST_12M	SMALLINT	2	B172
TD5BURK	DEBT_DAYS_NEXT_12M	SMALLINT	2	B173
TD5BURK	DEBTOR_DAYS_NA	CHAR	1	B173
TD5BURK	RETAINED_PROF_LOSS	DECIMAL	10	B174
TD5BURK	RETAIN_PROF_OR_LOS	CHAR	1	B175
TD5BURK	RETAINED_LOSS_CUST	VARCHAR	100	B175
TD5BUST	SALES_INC_LAST_12M	DECIMAL	10	B178
TD5BUST	REV_INC_SPLIT_CASH	SMALLINT	2	B181
TD5BUST	REV_INC_SPLIT_CRED	SMALLINT	2	B182
TD5BUST	BUSINESS_INC_CASH	SMALLINT	2	B184
TD5BUST	BUSINESS_INC_CRED	SMALLINT	2	B185
TD5BUST	SALES_PAID_TO_RBS	CHAR	1	B187
TD5BUST	SALES_NOT_RBS_PURC	CHAR	1	B187
TD5BUST	SALES_NOT_RBS_WAGE	CHAR	1	B188
TD5BUST	SALES_NOT_RBS_ANOT	CHAR	1	B188
TD5BUST	SALES_NOT_RBS_OTHE	CHAR	1	B188
TD5TRPO	ANY_DR_CR	CHAR	1	B189
TD5APCU	BORROWING_SINCE	DATE	4	B19
TD5TRPO	TOTAL_DUE	INTEGER	4	B190
TD5TRPO	TOTAL_NUMBER_PARTN	INTEGER	4	B191
TD5APCU	CONSOLIDATION	CHAR	1	B20
TD5TRPO	STATED_INVOICE_COL	SMALLINT	2	B208
TD5PLAN	DEBTOR_DAYS	CHAR	1	B208?
TD5TRPO	AVG_INVOICE_COLLEC	SMALLINT	2	B209
TD5APCU	CREDIT_CARD_PROB	CHAR	1	B21
TD5TRPO	LETTER_SEEKING_PAY	CHAR	1	B211
TD5TRPO	SOLICITORS_LETTER	CHAR	1	B211
TD5TRPO	COURT_ACTION	CHAR	1	B211
TD5TRPO	ACTION_OTHER	CHAR	1	B211
TD5TRPO	TOTAL_OVERDUE	INTEGER	4	B212

Appendix 5.3 Business Lending Checklist Variables (Ctd.)

TD5TRPO	TOT_AMT_BAD_DEBTS	INTEGER	4	B214
TD5TRPO	CURRENT_AMOUNT_BAD	INTEGER	4	B215
TD5TRPO	TOT_NO_BAD_DEBTS	INTEGER	4	B217
TD5TRPR	AMOUNT_OWED_IN_THO	INTEGER	4	B219
TD5PLAN	CREDITOR_DAYS	CHAR	1	B229?
TD5TRPO	CASH_ON_DELIVERY	CHAR	1	B235
TD5TRPO	REFUSAL_TO_SUPPLY	CHAR	1	B235
TD5BUST	VAT_UP_TO_DATE	CHAR	1	B238
TD5BUST	VAT_OUTSTANDING_AM	INTEGER	4	B238
TD5APPL	LOW_RISK_PROC_QUAL	CHAR	1	B23A
TD5RMAS	ACCOUNT_NO_UNVERIF	INTEGER	4	B24
TD5BUST	NI_PAYE_UP_TO_DATE	CHAR	1	B241
TD5BUST	NI_PAYE_OUTSTANDIN	INTEGER	4	B241
TD5BUST	TAX_PAY_UP_TO_DATE	CHAR	1	B244
TD5BUST	TAX_OUTSTANDING_AM	INTEGER	4	B244
TD5BUST	TAX_PAYABLE_NOTDUE	INTEGER	4	B246

Appendix 5.3 Ctd.

TD5BUST	TAX_DATE_DUE_1	DATE	4	B247
TD5BUST	TAX_DATE_DUE_2	DATE	4	B248
TD5BUST	BUS_OPERATE_WITHOU	CHAR	1	B249
TD5RMAS	MIN_LENDING_MARGIN	DECIMAL	6	B25
TD5BUST	CLOSE_FAMILY_MEMB	CHAR	1	B251
TD5BUST	KEY_EMPLOYEE	CHAR	1	B251
TD5BUST	OTHER_PRINCIPALS	CHAR	1	B251
TD5BUST	NO_PRINCIPALS_OTHE	CHAR	1	B251
TD5BUST	SICKNESS_DISABILIT	CHAR	1	B252
TD5BUST	INS_BUSINESSURE	CHAR	1	B253
TD5BUST	INS_KEYMAN	CHAR	1	B253
TD5BUST	INS_LIFE_COVER	CHAR	1	B253
TD5BUST	INS_PERSONAL_PERM	CHAR	1	B253
TD5BUST	INS_LOAN_GUARD	CHAR	1	B253
TD5BUST	INS_BUSINESS_LOAN	CHAR	1	B253
TD5BUST	INSURANCE_OTHER	CHAR	1	B253
TD5BUST	PROPRIETORS_OWNER	CHAR	1	B255
TD5RMAS	CUR_LENDING_MARGIN	DECIMAL	6	B26
TD5FACR	PROP_FACILITY_FEE	INTEGER	4	B28
TD5BUST	LOCAL_ECONOMY_FACT	CHAR	1	B295
TD5BUST	BUS_MILES_FROM_BR	SMALLINT	2	B297
TD5BUST	CUST_LACKS_FIN_CON	CHAR	1	B299
TD5BUST	MLM_SERVICE_CHARGE	CHAR	1	B301
TD5BUST	MLM_FAMILY_CONNECT	CHAR	1	B301
TD5BUST	MLM_DEPOSITS	CHAR	1	B301
TD5BUST	MLM_BG_ASSETS	CHAR	1	B301
TD5BUST	MLM_OTHER	CHAR	1	B301
TD5FISU	ACCOUNTING_YEAR_ST	DATE	4	B37

TD5FISU	ACCOUNTING_YEAR_EN	DATE	4	B38
TD5BUST	PROJ_SALE_NEXT_12M	DECIMAL	10	B41
TD5FISU	SALES_TURNOVER_SUB	INTEGER	4	B41
TD5FISU	GROSS_PROF_OR_LOSS	INTEGER	4	B42
TD5FISU	PROF_LOSS_PRE_DRAW	INTEGER	4	B43
TD5FISU	NET_PROFIT_OR_LOSS	INTEGER	4	B44
TD5FISU	BUS_DRAW_OR_REMUNE	INTEGER	4	B45
TD5FISU	PENSION_CONTRIB	INTEGER	4	B46
TD5FISU	INCREASED_CAPITAL	INTEGER	4	B47
TD5FISU	RET_PROF_OR_SURPL	INTEGER	4	B48
TD5FISU	TRADE_DEBTORS	INTEGER	4	B49
TD5FISU	TRADE_CREDITORS	INTEGER	4	B50
TD5FISU	TOT_ACC_OR_NTA_NET	INTEGER	4	B61
TD5BREQ	WORKING_CAPITAL	CHAR	1	B67
TD5FATY	PURPOSE	CHAR	4	B67,B90
TD5BUST	BORROWING_PURPOSE	CHAR	1	B67-B90
TD5BREQ	WORKING_CAPITAL_ST	CHAR	1	B68
TD5BREQ	WORKING_CAPITAL_DE	CHAR	1	B68
TD5BREQ	WORKING_CAPITAL_CR	CHAR	1	B68
TD5BREQ	ASSET_PURCHASE	CHAR	1	B68A
TD5BREQ	DEBT_RESCHEDULING	CHAR	1	B78
TD5BREQ	PURCH_CAP_OF_BUS	CHAR	1	B83
TD5BREQ	OTHER_REAS_TO_BORR	CHAR	1	B87
TD5BREQ	SOURCE_NONE	CHAR	1	B91
TD5BREQ	SOURCE_BORROWED	CHAR	1	B92

Appendix 5.3 Ctd.

TD5BREQ	SOURCE_NON_BORROWD	CHAR	1	B93
TD5BREQ	BORROWED_SOURCE	CHAR	30	B94
TD5BREQ	BORROWED_AMOUNT	INTEGER	4	B95
TD5BREQ	NON_BORROWED_SOURC	CHAR	30	B96
TD5BREQ	NON_BORROWED_AMOUN	INTEGER	4	B97
TD5BREQ	REPAY_EXIST_LEVELS	CHAR	1	B98
TD5BREQ	REPAY_OTHER_INCOME	CHAR	1	B99

Appendices to Chapter 6 (Appendix 6.1, 6.2. 6.3)

Appendix 6.1

WOE for Ever Grade E (Assets and collateral)

ODVGROUP (OTHDV)			
	Missing	GE 1	Total
Goods	410	242	652
	70.69	69.14	
Bads	170	108	278
	23.31	350	
Total	580		930
gij/bij	2.411764706	2.240740741	
ln(gij/bij)	0.880358723	0.806806499	
Bj/Gj	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	0.027935274	-0.045616949	

NBGROUP (NONBORR)	Missing	LE 9,000	LE 27,000	GT 27,000	Total
Goods	358	95	95	104	652
	67.29	77.87	73.08	71.23	
Bads	174	27	35	42	278
	32.71	22.13	26.92	28.77	
Total	532	122	130	146	930
gij/bij	2.057471264	3.518518519	2.714285714	2.47619	
ln(gij/bij)	0.721477687	1.258040026	0.99852883	0.906721	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	-0.130945761	0.405616577	0.146105382	0.054298	

ACLGROUP	0	LE 40000	LE 90000	GT 90000	Total
Goods	408	83	79	82	652
	70.96	65.87	69.91	70.69	
Bads	167	43	34	34	278
	29.04	34.13	30.09	29.31	
Total	575	126	113	116	930
gij/bij	2.443113772	1.930232558	2.323529412	2.411765	
ln(gij/bij)	0.893273362	0.657640492	0.843087328	0.880359	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	0.040849914	-0.194782956	-0.00933612	0.027935	

LDOGROUP	Owned	Leased	Missing		
Goods	153	137	362	652	
	71.5	71.35	69.08		
Bads	61	55	162	278	
	28.5	28.65	30.92		
Total	214	192	524	930	
gij/bij	2.508196721	2.490909091	2.234567901		
ln(gij/bij)	0.919564057	0.912647741	0.804047877		
Bj/Gj	0.426380368	0.426380368	0.426380368		
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448		
ln(gij/bij) + ln(Bj/Gj)	0.067140609	0.060224292	-0.048375572		

BPVGROUP	0	LE 30,000	LE 60,000	LE 120,000	GT 120,000
Goods	314	153	39	52	94
	69.16	71.83	67.24	71.23	71.21
Bads	140	60	19	21	38
	30.84	28.17	32.76	28.77	28.79
Total	454	213	58	73	132
gij/bij	2.242857143	2.55	2.052631579	2.47619	2.473684
ln(gij/bij)	0.807750563	0.936093359	0.719122667	0.906721	0.905709
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638	0.42638
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423	-0.852423
ln(gij/bij) + ln(Bj/Gj)	-0.044672885	0.083669911	-0.133300781	0.054298	0.053285

WOE for Ever Grade E (Accounting)

RYEGROUP (RECYRE)			
	Missing	Accounts available	Total
Goods	438	214	652
	70.76	68.81	
Bads	181	97	278
	29.24	31.19	
Total	619	311	930
gij/bij	2.419889503	2.206185567	
ln(gij/bij)	0.883721879	0.791265037	
Bj/Gj	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	0.031298431	-0.061158412	

PYEGROUP (PASYRE)			
	Missing	Accounts available	Total
Goods	448	204	652
	71.11	68	
Bads	182	96	278
	28.89	32	
Total	630	300	930
gij/bij	2.461538462	2.125	
ln(gij/bij)	0.900786545	0.753771802	
Bj/Gj	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	0.048363097	-0.098651646	

PNPGROUP (PASNP)	Missing	Negative	0	LE 100,000	GT 100,000	Total
Goods	448	44	55	58	47	652
	71.11	75.86	57.89	69.05	74.6	
Bads	182	14	40	26	16	278
	28.89	24.14	42.11	30.95	25.4	
Total	630	58	95	84	63	930
gij/bij	2.461538462	3.142857143	1.375	2.23076923	2.9375	
ln(gij/bij)	0.900786545	1.145132304	0.318453731	0.80234647	1.077559	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	0.048363097	0.292708856	-0.533969717	-0.050077	0.225135	

PPLGROUP (PASPL)	0 or missing	LT 20000	GT 20000			
Goods	429	33	48	47	53	42
	70.91	58.93	77.42	64.38	68.83	73.68
Bads	176	23	14	26	24	15
	29.09	41.07	22.58	35.62	31.17	26.32
Total	605	56	62	73	77	57
gij/bij	2.4375	1.434782609	3.428571429	1.80769231	2.208333	2.8
ln(gij/bij)	0.890972924	0.361013346	1.232143681	0.59205106	0.792238	1.029619
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	0.42638	0.42638
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	-0.852423	-0.852423
ln(gij/bij) + ln(Bj/Gj)	0.038549476	-0.491410103	0.379720233	-0.2603724	-0.060185	0.177196

PRPGROUP (PASRP)	Missing					Total
Goods	439	36	116	13	48	652
	71.04	70.59	66.29	54.17	77.42	
Bads	179	15	59	11	14	278
	28.96	29.41	33.71	45.83	22.58	
Total	618	51	175	24	62	930
gij/bij	2.452513966	2.4	1.966101695	1.18181818	3.428571	
ln(gij/bij)	0.897113607	0.875468737	0.676052747	0.16705408	1.232144	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	0.044690159	0.023045289	-0.176370701	-0.6853694	0.37972	

PSTGROUP (PASST)	Missing	0	GE 1 LT 90,000	GE 90,000	Total
Goods	108	332	92	120	652
	64.29	72.33	70.77	69.36	
Bads	60	127	38	53	278
	35.71	27.67	29.23	30.64	
Total	168	459	130	173	930
gij/bij	1.8	2.614173228	2.421052632	2.26415094	
ln(gij/bij)	0.587786665	0.960947882	0.884202417	0.81719983	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	
ln(gij/bij) + ln(Bj/Gj)	-0.264636783	0.108524434	0.031778969	-0.0352236	

PTAGROUP(PASTA)					Total
Goods	448	67	49	88	652
	71.11	57.76	77.78	72.73	
Bads	182	49	14	33	278
	28.89	42.24	22.22	27.27	
Total	630	116	63	121	930
gij/bij	2.461538462	1.367346939	3.5	2.66666667	
ln(gij/bij)	0.900786545	0.312872321	1.252762968	0.98082925	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	
ln(gij/bij) + ln(Bj/Gj)	0.048363097	-0.539551127	0.40033952	0.1284058	

RNPGROUP (RECNP)	Missing	Negative	LE 13,000	GT 13,000	Total
Goods	438	90	76	48	652
	70.76	62.5	78.35	68.57	
Bads	181	54	21	22	278
	29.24	37.5	21.65	31.43	
Total	619	144	97	70	930
gij/bij	2.419889503	1.666666667	3.619047619	2.18181818	
ln(gij/bij)	0.883721879	0.510825624	1.286210903	0.78015856	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	
ln(gij/bij) + ln(Bj/Gj)	0.031298431	-0.341597824	0.433787454	-0.0722649	

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RPLGROUP (RECPL)	Missing	Negative	LE 13,000	LE 24,000	GT 24,000	Total
Goods	419	27	57	51	98	652
	70.9	58.7	76	63.75	71.01	
Bads	172	19	18	29	40	278
	29.1	41.3	24	36.25	28.99	
Total	591	46	75	80	138	930
gij/bij	2.436046512	1.421052632	3.166666667	1.75862069	2.45	
ln(gij/bij)	0.890376443	0.351397887	1.15267951	0.5645298	0.896088	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	0.037952995	-0.501025561	0.300256062	-0.2878936	0.043665	

RRPGROUP (RECRP)	Missing	Negative	LE 9,000	GT 9,000	Total
Goods	429	131	42	50	652
	70.68	65.17	77.78	73.53	
Bads	178	70	12	18	278
	29.32	34.83	22.22	26.47	
Total	607	201	54	68	930
gij/bij	2.41011236	1.871428571	3.5	2.77777778	
ln(gij/bij)	0.879673369	0.626702081	1.252762968	1.02165125	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	
ln(gij/bij) + ln(Bj/Gj)	0.02724992	-0.225721367	0.40033952	0.1692278	

RSTGROUP (RECST)	Missing or 0	LE 100,000	GT 100,000	Total
Goods	430	97	125	652
	70.26	68.31	71.02	
Bads	182	45	51	278
	29.74	31.69	28.98	
Total	612	142	176	930
gij/bij	2.362637363	2.155555556	2.450980392	
ln(gij/bij)	0.859778522	0.768048489	0.896488105	
Bj/Gj	0.426380368	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	0.007355073	-0.08437496	0.044064656	

RTAGROUP (RECTA)	Missing	Negative	LE 16,000	GT 16,000	Total
Goods	438	64	53	97	652
	70.76	57.66	76.81	74.05	
Bads	181	47	16	34	278
	29.24	42.34	23.19	25.95	
Total	619	111	69	131	930
gij/bij	2.419889503	1.361702128	3.3125	2.85294118	
ln(gij/bij)	0.883721879	0.308735482	1.197703191	1.04835045	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	
ln(gij/bij) + ln(Bj/Gj)	0.031298431	-0.543687967	0.345279743	0.19592701	

PGPGROUP (PASGP)	0 or Missing	LE 25,000	LE 50,000	LE 100,000	GT 100,000	Total
Goods	478	34	45	55	40	652
	69.99	70.83	66.18	73.33	71.43	
Bads	205	14	23	20	16	278
	30.01	29.17	33.82	26.67	28.57	
Total	683	48	68	75	56	930
gij/bij	2.331707317	2.428571429	1.956521739	2.75	2.5	
ln(gij/bij)	0.846600753	0.887303195	0.671168274	1.01160091	0.916291	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	-0.005822695	0.034879747	-0.181255174	0.15917746	0.063867	

RGPGROUP (RECGP)	Missing	0	LE 27,000	LE 50,000	GT 50,000	Total
Goods	425	40	40	39	108	652
	70.83	60.61	76.92	57.35	75	
Bads	175	26	12	29	36	278
	29.17	39.39	23.08	42.65	25	
Total	600	66	52	68	144	930
gij/bij	2.428571429	1.538461538	3.333333333	1.34482759	3	
ln(gij/bij)	0.887303195	0.430782916	1.203972804	0.29626582	1.098612	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	0.034879747	-0.421640532	0.351549356	-0.5561576	0.246189	

PSDGROUP (PASBD)	Missing	0	LE 15,000	LE 27,000	GT 27,000	Total
Goods	442	67	52	42	49	652
	71.18	62.04	68.42	72.41	73.13	
Bads	179	41	24	16	18	278
	28.82	37.96	31.58	27.59	26.87	
Total	621	108	76	58	67	930
gij/bij	2.469273743	1.634146341	2.166666667	2.625	2.722222	
ln(gij/bij)	0.903924076	0.491120553	0.773189888	0.9650809	1.001449	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638037	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.8524234	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	0.051500628	-0.361302896	-0.07923356	0.11265745	0.149025	

WOE for Ever Grade E (Entrepreneur)

AGEGROUP(AGE1)	Missing	18-37	LE 50	GT 50	Total
Goods	343	97	136	76	652
	68.74	69.29	72.73	73.08	
Bads	156	43	51	28	278
	31.26	30.71	27.27	26.92	
Total	499	140	187	104	930
gij/bij	2.198717949	2.255813953	2.666666667	2.714286	
ln(gij/bij)	0.78787444	0.813510863	0.980829253	0.998529	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	-0.064549008	-0.038912585	0.128405805	0.146105	

DYRGROUP(DOB1YR)	Missing	LE 15	GT 15	Total
Goods	471	116	65	652
	69.88	71.17	69.89	
Bads	203	47	28	278
	30.12	28.83	30.11	
Total	674	163	93	930
gij/bij	2.320197044	2.468085106	2.321428571	
ln(gij/bij)	0.841652115	0.903442589	0.84218276	
Bj/Gj	0.426380368	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	-0.010771333	0.051019141	-0.010240689	

DPRGROUP(DOB1PER)	Missing	LE 75	GT 75	Total
Goods	354	169	129	652
	69.28	69.26	73.71	
Bads	157	75	46	278
	30.72	30.74	26.29	
Total	511	244	175	930
gij/bij	2.25477707	2.253333333	2.804347826	
ln(gij/bij)	0.813051108	0.812410601	1.031171008	
Bj/Gj	0.426380368	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	-0.03937234	-0.040012847	0.17874756	

DYIGROUP(DOB1YI)	Missing	1-7	GT 7	Total
Goods	460	86	106	652
	68.76	70.49	76.26	
Bads	209	36	33	278
	31.24	29.51	23.74	
Total	669	122	139	930
gij/bij	2.200956938	2.388888889	3.212121212	
ln(gij/bij)	0.788892238	0.870828358	1.166931533	
Bj/Gj	0.426380368	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	-0.063531211	0.01840491	0.314508084	

PNRGROUP (PARTNER)			
	No partner	Has partner	Total
Goods	486	166	652
	70.43	69.17	
Bads	204	74	278
	29.57	30.83	
Total	690	240	930
gij/bij	2.382352941	2.243243243	
ln(gij/bij)	0.86808863	0.807922695	
Bj/Gj	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	0.015665182	-0.044500753	

x

WOE for Ever Grade E (Distance and Miscellaneous)

RTNGROUP (RETAIN)	0	LE 4000	LE 10000	LE 40000	GT 40000	Total
Goods	295	93	115	125	24	652
	70.41	70.99	69.28	71.84	60	
Bads	124	38	51	49	16	278
	29.59	29.01	30.72	28.16	40	
Total	419	131	166	174	40	930
gij/bij	2.379032258	2.447368421	2.254901961	2.55102	1.5	
ln(gij/bij)	0.866693791	0.895013333	0.813106496	0.936493	0.40546511	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638	0.42638037	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423	-0.8524234	
ln(gij/bij) + ln(Bj/Gj)	0.014270342	0.042589885	-0.039316953	0.08407	-0.4469583	

SINGROUP (SALESIN)	0	LE 20000	LE 60000	GT 60000	
Goods	372	46	75	159	652
	71.4	74.19	65.22	68.53	
Bads	149	16	40	73	278
	28.6	25.81	34.78	31.47	
Total	521	62	115	232	930
gij/bij	2.496644295	2.875	1.875	2.178082	
ln(gij/bij)	0.914947548	1.056052674	0.628608659	0.778445	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	0.0625241	0.203629226	-0.223814789	-0.073979	

PJSGROUP (PROJSAL)	0	LE 25000	LE 50000	LE 90000	GT 90000	Total
Goods	208	72	89	78	205	652
	71.97	64.86	71.77	69.03	69.97	
Bads	81	39	35	35	88	278
	28.03	35.14	28.23	30.97	30.03	
Total	289	111	124	113	293	930
gij/bij	2.567901235	1.846153846	2.542857143	2.228571	2.32954545	
ln(gij/bij)	0.943088925	0.613104473	0.933288308	0.801361	0.84567316	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638	0.42638037	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423	-0.8524234	
ln(gij/bij) + ln(Bj/Gj)	0.090665477	-0.239318975	0.08086486	-0.051063	-0.0067503	

BSMGROUP (BUSMILE)	0	LE 2	LE 6	GT 6	Total
Goods	125	150	159	218	652
	75.3	69.77	73.95	65.27	
Bads	41	65	56	116	278
	24.7	30.23	26.05	34.73	
Total	166	215	215	334	930
gij/bij	3.048780488	2.307692308	2.839285714	1.87931	
ln(gij/bij)	1.114741671	0.836248024	1.043552511	0.630905	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	0.262318222	-0.016175424	0.191129063	-0.221519	

CPRGROUP (CREDPER)	0	Missing	LE 50	LE 95	GT 95	
Goods	278	134	65	45	130	652
	66.35	74.86	78.31	72.58	69.52	
Bads	141	45	18	17	57	278
	33.65	25.14	21.69	27.42	30.48	
Total	419	179	83	62	187	930
gij/bij	1.971631206	2.977777778	3.611111111	2.647059	2.28070175	
ln(gij/bij)	0.678861223	1.09117731	1.284015512	0.973449	0.82448318	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.42638	0.42638037	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423	-0.8524234	
ln(gij/bij) + ln(Bj/Gj)	-0.173562225	0.238753862	0.431592064	0.121026	-0.0279403	

WOE for Ever Grade E (Exposure)

OLNGROUP (OTH_LN)			
	Has no other loan	Has other loan	Total
Goods	514	138	652
	69.93	70.77	
Bads	221	57	278
	30.07	29.23	
Total	735	195	930
gij/bij	2.325791855	2.421052632	
ln(gij/bij)	0.844060564	0.884202417	
Bj/Gj	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	-0.008362884	0.031778969	

NDRGROUP (NODUR)			
	Has facility of no duration	Has no facility of no duration	Total
Goods	573	79	652
	69.12	78.22	
Bads	256	22	278
	30.88	21.78	
Total	829	101	930
gij/bij	2.23828125	3.590909091	
ln(gij/bij)	0.805708272	1.278405399	
Bj/Gj	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	-0.046715176	0.425981951	

CDP_GROUP			
	0 or missing	GT 0	Total
Goods	412	240	652
	68.9	72.29	
Bads	186	92	278
	31.1	27.71	
Total	598	332	930
gij/bij	2.215053763	2.608695652	
ln(gij/bij)	0.795276676	0.958850346	
Bj/Gj	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	-0.057146773	0.106426898	

AGRGROUP(AGGBORR)	LE 3000	LE 30,000	LE 90,000	GT 90,000	Total
Goods	91	261	167	133	652
	64.08	72.1	68.16	73.48	
Bads	51	101	78	48	278
	35.92	27.9	31.84	26.52	
Total	142	362	245	181	930
gij/bij	1.784313725	2.584158416	2.141025641	2.770833333	
ln(gij/bij)	0.579033874	0.94939989	0.761284986	1.019148117	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	-0.273389574	0.096976442	-0.091138463	0.166724669	

CXPGROUP (CUSEXP)	0	LE 15,000	LE 60,000	GT 60,000	Total
Goods	151	204	163	134	652
	68.95	71.08	70.26	69.79	
Bads	68	83	69	58	278
	31.05	28.92	29.74	30.21	
Total	219	287	232	192	930
gij/bij	2.220588235	2.457831325	2.362318841	2.310344828	
ln(gij/bij)	0.797772132	0.899279386	0.859643696	0.837396789	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	-0.054651317	0.046855938	0.007220248	-0.015026659	

BODGROUP (BUS_OD)	0 or missing	LE 5,000	GT 5000	
Goods	380	140	132	652
	70.37	68.97	70.59	
Bads	160	63	55	278
	29.63	31.03	29.41	
Total	540	203	187	930
gij/bij	2.375	2.222222222	2.4	
ln(gij/bij)	0.864997437	0.798507696	0.875468737	
Bj/Gj	0.426380368	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	0.012573989	-0.053915752	0.023045289	

TAGGROUP(TOTALAG)	LT 4,000	LE 10,000	LE 40000	LE 100000	GT 100000	Total
Goods	109	94	188	136	125	652
	66.06	73.44	70.41	69.04	72.25	
Bads	56	34	79	61	48	278
	33.94	26.56	29.59	30.96	27.75	
Total	165	128	267	197	173	930
gij/bij	1.946428571	2.764705882	2.379746835	2.229508197	2.604167	
ln(gij/bij)	0.665996191	1.016934258	0.86699411	0.801781022	0.957113	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.426380368	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423448	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	-0.186427257	0.164510809	0.014570662	-0.050642427	0.104689	

NSMGROUP(NEWSUM)	LE 4000	LE 10000	LE 40000	LE 100000	GT 100000	
Goods	132	105	191	134	90	652
	66.33	75.54	69.2	71.66	69.77	
Bads	67	34	85	53	39	278
	33.67	24.46	30.8	28.34	30.23	
Total	199	139	276	187	129	930
gij/bij	1.970149254	3.088235294	2.247058824	2.528301887	2.307692	
ln(gij/bij)	0.678109303	1.127599826	0.809622172	0.927547886	0.836248	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.426380368	0.42638	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423448	-0.852423	
ln(gij/bij) + ln(Bj/Gj)	-0.174314145	0.275176377	-0.042801277	0.075124438	-0.016175	

BLNGROUP	0 or missing	LE 10000	LE 50000	GT 50000	Total
Goods	328	30	143	151	652
	68.91	71.43	72.59	70.23	
Bads	148	12	54	64	278
	31.09	28.57	27.41	29.77	
Total	476	42	197	215	930
gij/bij	2.216216216	2.5	2.648148148	2.359375	
ln(gij/bij)	0.795801335	0.916290732	0.973860584	0.858396753	
Bj/Gj	0.426380368	0.426380368	0.426380368	0.426380368	
ln(Bj/Gj)	-0.852423448	-0.852423448	-0.852423448	-0.852423448	
ln(gij/bij) + ln(Bj/Gj)	-0.056622114	0.063867284	0.121437135	0.005973305	

Appendix 6.2
WOE grade F (Assets and Collateral)

ODVGROUP (OTHDV)			
	Missing	GE 1	Total
Goods	501	289	790
	86.38	82.57	
Bads	79	61	140
	13.62	17.43	
Total	580	350	930
gij/bij	6.341772152	4.737704918	
ln(gij/bij)	1.847158249	1.555552824	
Bj/Gj	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.116767726	-0.174837699	

NBGROUP (NONBORR)	Missing or 0	LE 9,000	LE 27,000	GT 27,000	Total
Goods	451	108	110	121	790
	84.77	88.52	84.62	82.88	
Bads	81	14	20	25	140
	15.23	11.48	15.38	17.12	
Total	532	122	130	146	930
gij/bij	5.567901235	7.714285714	5.5	4.84	
ln(gij/bij)	1.717018185	2.043073898	1.704748092	1.576915	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	-0.013372338	0.312683375	-0.025642431	-0.153476	

ACLGROUP	0	LE 40000	LE 90000	GT 90000	Total
Goods	498	104	90	98	790
	86.61	82.54	79.65	84.48	
Bads	77	22	23	18	140
	13.39	17.46	20.35	15.52	
Total	575	126	113	116	930
gij/bij	6.467532468	4.727272727	3.913043478	5.444444	
ln(gij/bij)	1.866794655	1.553348446	1.364315454	1.694596	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.136404132	-0.177042077	-0.366075068	-0.035795	

LDOGROUP	Owned	Leased	Missing	
Goods	184	169	437	790
	85.98	88.02	83.4	
Bads	30	23	87	140
	14.02	11.98	16.6	
Total	214	192	524	930
gij/bij	6.133333333	7.347826087	5.022988506	
ln(gij/bij)	1.813738376	1.994404499	1.614025076	
Bj/Gj	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.083347853	0.264013976	-0.116365446	

BPVGROUP	0	LE 30,000	LE 60,000	LE 120,000	GT 120,000	Total
Goods	386	187	45	64	108	790
	85.02	87.79	77.59	87.67	81.82	
Bads	68	26	13	9	24	140
	14.98	12.21	22.41	12.33	18.18	
Total	454	213	58	73	132	930
gij/bij	5.676470588	7.192307692	3.461538462	7.111111	4.5	
ln(gij/bij)	1.736329664	1.973012079	1.241713132	1.961659	1.504077	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.177215	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730391	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.005939141	0.242621556	-0.488677391	0.231268	-0.226313	

WOE grade F (Accounting)

RYEGROUP (RECYRE)			
	Missing	Accounts available	Total
Goods	530	260	790
	85.62	83.6	
Bads	89	51	140
	14.38	16.4	
Total	619	311	930
gij/bij	5.95505618	5.098039216	
ln(gij/bij)	1.784240637	1.628855998	
Bj/Gj	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.053850114	-0.101534525	

PYEGROUP (PASYRE)			
	Missing	Accounts available	Total
Goods	540	250	790
	85.71	83.33	
Bads	90	50	140
	14.29	16.67	
Total	630	300	930
gij/bij	6	5	
ln(gij/bij)	1.791759469	1.609437912	
Bj/Gj	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.061368946	-0.12095261	

PNPGROUP (PASNP)	Missing	Negative	0	LE 100,000	GT 100,000	Total
Goods	540	53	70	70	57	790
	85.71	91.38	73.68	83.33	90.48	
Bads	90	5	25	14	6	140
	14.29	8.62	26.32	16.67	9.52	
Total	630	58	95	84	63	930
gij/bij	6	10.6	2.8	5	9.5	
ln(gij/bij)	1.791759469	2.360854001	1.029619417	1.60943791	2.251292	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.061368946	0.630463478	-0.700771106	-0.1209526	0.520901	

PPLGROUP (PASPL)	0 or missing	LT 20000	GT 20000				
Goods	518	46	55	57	61	53	790
	85.62	82.14	88.71	78.08	79.22	92.98	
Bads	87	10	7	16	16	4	140
	14.38	17.86	11.29	21.92	20.78	7.02	
Total	605	56	62	73	77	57	930
gij/bij	5.954022989	4.6	7.857142857	3.5625	3.8125	13.25	
ln(gij/bij)	1.784067124	1.526056303	2.061423036	1.27046255	1.338285	2.583998	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	0.177215	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	-1.730391	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.053676601	-0.204334219	0.331032513	-0.459928	-0.392105	0.853607	

PRPGROUP (PASRP)	Missing					Total
Goods	530	44	141	19	56	790
	85.76	86.27	80.57	79.17	90.32	
Bads	88	7	34	5	6	140
	14.24	13.73	19.43	20.83	9.68	
Total	618	51	175	24	62	930
gij/bij	6.022727273	6.285714286	4.147058824	3.8	9.333333	
ln(gij/bij)	1.795540192	1.838279485	1.422399366	1.33500107	2.233592	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.065149669	0.107888962	-0.307991157	-0.3953895	0.503202	

PSTGROUP (PASST)	Missing				Total
Goods	139	397	110	144	790
	82.74	86.49	84.62	83.24	
Bads	29	62	20	29	140
	17.26	13.51	15.38	16.76	
Total	168	459	130	173	930
gij/bij	4.793103448	6.403225806	5.5	4.96551724	
ln(gij/bij)	1.567178103	1.856801896	1.704748092	1.60251747	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	
ln(gij/bij) + ln(Bj/Gj)	-0.16321242	0.126411373	-0.025642431	-0.1278731	

PTAGROUP(PASTA)					Total
Goods	540	88	56	106	790
	85.71	75.86	88.89	87.6	
Bads	90	28	7	15	140
	14.29	24.14	11.11	12.4	
Total	630	116	63	121	930
gij/bij	6	3.142857143	8	7.06666667	
ln(gij/bij)	1.791759469	1.145132304	2.079441542	1.95538889	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	
ln(gij/bij) + ln(Bj/Gj)	0.061368946	-0.585258219	0.349051019	0.22499837	

RNPGROUP (RECNP)	Missing	Negative	LE 13,000	GT 13,000	Total
Goods	530	112	87	61	790
	85.62	77.78	89.69	87.14	
Bads	89	32	10	9	140
	14.38	22.22	10.31	12.86	
Total	619	144	97	70	930
gij/bij	5.95505618	3.5	8.7	6.77777778	
ln(gij/bij)	1.784240637	1.252762968	2.163323026	1.91364929	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	
ln(gij/bij) + ln(Bj/Gj)	0.053850114	-0.477627554	0.432932503	0.18325876	

RPLGROUP (RECPL)	Missing	Negative	LE 13,000	LE 24,000	GT 24,000	Total
Goods	507	36	68	62	117	790
	85.79	78.26	90.67	77.5	84.78	
Bads	84	10	7	18	21	140
	14.21	21.74	9.33	22.5	15.22	
Total	591	46	75	80	138	930
gij/bij	6.035714286	3.6	9.714285714	3.44444444	5.571429	
ln(gij/bij)	1.797694205	1.280933845	2.273597556	1.23676263	1.717651	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.067303682	-0.449456677	0.543207033	-0.4936279	-0.012739	

RRPGROUP (RECRP)	Missing	Negative	LE 9,000	GT 9,000	Total
Goods	520	160	50	60	790
	85.67	79.6	92.59	88.24	
Bads	87	41	4	8	140
	14.33	20.4	7.41	11.76	
Total	607	201	54	68	930
gij/bij	5.977011494	3.902439024	12.5	7.5	
ln(gij/bij)	1.787920693	1.361601749	2.525728644	2.01490302	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	
ln(gij/bij) + ln(Bj/Gj)	0.05753017	-0.368788774	0.795338121	0.2845125	

RSTGROUP (RECST)	Missing or 0	LE 100,000	GT 100,000	Total
Goods	525	117	148	790
	85.78	82.39	84.09	
Bads	87	25	28	140
	14.22	17.61	15.91	
Total	612	142	176	930
gij/bij	6.034482759	4.68	5.285714286	
ln(gij/bij)	1.797490144	1.54329811	1.665007764	
Bj/Gj	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.067099621	-0.187092413	-0.065382759	

RTAGROUP (RECTA)	Missing	Negative	LE 16,000	GT 16,000	Total
Goods	530	83	60	117	790
	85.62	74.77	86.96	89.31	
Bads	89	28	9	14	140
	14.38	25.23	13.04	10.69	
Total	619	111	69	131	930
gij/bij	5.95505618	2.964285714	6.666666667	8.35714286	
ln(gij/bij)	1.784240637	1.086636098	1.897119985	2.12311661	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	
ln(gij/bij) + ln(Bj/Gj)	0.053850114	-0.643754425	0.166729462	0.39272608	

PGPGROUP (PASGP)	0 or Missing	LE 25,000	LE 50,000	LE 100,000	GT 100,000	Total
Goods	584	39	54	62	51	790
	85.51	81.25	79.41	82.67	91.07	
Bads	99	9	14	13	5	140
	14.49	18.75	20.59	17.33	8.93	
Total	683	48	68	75	56	930
gij/bij	5.898989899	4.333333333	3.857142857	4.76923077	10.2	
ln(gij/bij)	1.774781133	1.466337069	1.349926717	1.56218503	2.322388	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.04439061	-0.264053454	-0.380463806	-0.1682055	0.591997	

RGPGROUP (RECGP)	Missing	0	LE 27,000	LE 50,000	GT 50,000	Total
Goods	515	54	45	51	125	790
	85.83	81.82	86.54	75	86.81	
Bads	85	12	7	17	19	140
	14.17	18.18	13.46	25	13.19	
Total	600	66	52	68	144	930
gij/bij	6.058823529	4.5	6.428571429	3	6.578947	
ln(gij/bij)	1.801515644	1.504077397	1.860752341	1.09861229	1.883875	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.071125121	-0.226313126	0.130361818	-0.6317782	0.153484	

PSDGROUP (PASBD)	Missing	0	LE 15,000	LE 27,000	GT 27,000	Total
Goods	533	82	65	50	60	790
	85.83	75.93	85.53	86.21	89.55	
Bads	88	26	11	8	7	140
	14.17	24.07	14.47	13.79	10.45	
Total	621	108	76	58	67	930
gij/bij	6.056818182	3.153846154	5.909090909	6.25	8.571429	
ln(gij/bij)	1.80118461	1.148622709	1.776491997	1.83258146	2.148434	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.070794087	-0.581767814	0.046101474	0.10219094	0.418044	

WOE Ever F (Entrepreneur)

AGEGROUP(AGE1)	Missing	18-37	LE 50	GT 50	Total
Goods	423	119	162	86	790
	84.77	85	86.63	82.69	
Bads	76	21	25	18	140
	15.23	15	13.37	17.31	
Total	499	140	187	104	930
gij/bij	5.565789474	5.666666667	6.48	4.7777778	
ln(gij/bij)	1.716638839	1.734601055	1.86872051	1.5639755	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.1772152	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.7303905	
ln(gij/bij) + ln(Bj/Gj)	-0.013751684	0.004210533	0.138329988	-0.166415	

DYRGROUP(DOB1YR)	Missing	LE 15	GT 15	Total
Goods	577	136	77	790
	85.61	83.44	82.8	
Bads	97	27	16	140
	14.39	16.56	17.2	
Total	674	163	93	930
gij/bij	5.948453608	5.037037037	4.8125	
ln(gij/bij)	1.783131288	1.61681802	1.5712167	
Bj/Gj	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.052740765	-0.113572503	-0.159173823	

DPRGROUP(DOB1PER)	Missing	LE 75	GT 75	Total
Goods	435	199	156	790
	85.13	81.56	89.14	
Bads	76	45	19	140
	14.87	18.44	10.86	
Total	511	244	175	930
gij/bij	5.723684211	4.422222222	8.210526316	
ln(gij/bij)	1.744612691	1.486642335	2.105417028	
Bj/Gj	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.014222168	-0.243748188	0.375026505	

DYIGROUP(DOB1YI)	Missing	1-7	GT 7	Total
Goods	564	105	121	790
	84.3	86.07	87.05	
Bads	105	17	18	140
	15.7	13.93	12.95	
Total	669	122	139	930
gij/bij	5.371428571	6.176470588	6.722222222	
ln(gij/bij)	1.681093901	1.820747006	1.905418788	
Bj/Gj	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	-0.049296622	0.090356483	0.175028265	

PNRGROUP (PARTNER)				
	No partner	Has partner	Total	
Goods	595	195	790	
	86.23	81.25		
Bads	95	45	140	
	13.77	18.75		
Total	690	240	930	
gij/bij	6.263157895	4.333333333		
ln(gij/bij)	1.834684514	1.466337069		
Bj/Gj	0.17721519	0.17721519		
ln(Bj/Gj)	-1.730390523	-1.730390523		
ln(gij/bij) + ln(Bj/Gj)	0.104293991	-0.264053454		

WOE Ever F (Distance and Miscellaneous)

RTNGROUP (RETAIN)	0	LE 4000	LE 10000	LE 40000	GT 40000	Total
Goods	354	114	143	147	32	790
	84.49	87.02	86.14	84.48	80	
Bads	65	17	23	27	8	140
	15.51	12.98	13.86	15.52	20	
Total	419	131	166	174	40	930
gij/bij	5.446153846	6.705882353	6.217391304	5.444444	4	
ln(gij/bij)	1.694909643	1.902985104	1.827350414	1.694596	1.38629436	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.177215	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730391	-1.7303905	
ln(gij/bij) + ln(Bj/Gj)	-0.03548088	0.172594581	0.096959891	-0.035795	-0.3440962	

SINGROUP (SALESIN)	0	LE 20000	LE 60000	GT 60000	
Goods	445	51	98	196	790
	85.41	82.26	85.22	84.48	
Bads	76	11	17	36	140
	14.59	17.74	14.78	15.52	
Total	521	62	115	232	930
gij/bij	5.855263158	4.636363636	5.764705882	5.444444	
ln(gij/bij)	1.767340942	1.53393036	1.751754135	1.694596	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.036950419	-0.196460163	0.021363612	-0.035795	

PJSGROUP (PROJSAL)	0	LE 25000	LE 50000	LE 90000	GT 90000	Total
Goods	251	88	107	98	246	790
	86.85	79.28	86.29	86.73	83.96	
Bads	38	23	17	15	47	140
	13.15	20.72	13.71	13.27	16.04	
Total	289	111	124	113	293	930
gij/bij	6.605263158	3.826086957	6.294117647	6.533333	5.23404255	
ln(gij/bij)	1.887866779	1.341842599	1.83961549	1.876917	1.65518393	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.177215	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730391	-1.7303905	
ln(gij/bij) + ln(Bj/Gj)	0.157476257	-0.388547924	0.109224968	0.146527	-0.0752066	

BSMGROUP (BUSMILE)	0	LE 2	LE 6	GT 6	Total
Goods	146	179	184	281	790
	87.95	83.26	85.58	84.13	
Bads	20	36	31	53	140
	12.05	16.74	14.42	15.87	
Total	166	215	215	334	930
gij/bij	7.3	4.972222222	5.935483871	5.301887	
ln(gij/bij)	1.987874348	1.603866867	1.780948553	1.668063	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.257483825	-0.126523655	0.05055803	-0.062328	

CPRGROUP (CREDPER)	0	Missing	LE 50	LE 95	GT 95	
Goods	341	158	72	51	168	790
	81.38	88.27	86.75	82.26	89.84	
Bads	87	21	11	11	19	140
	18.62	11.73	13.25	17.74	10.16	
Total	428	179	83	62	187	930
gij/bij	3.91954023	7.523809524	6.545454545	4.636364	8.84210526	
ln(gij/bij)	1.365974359	2.018072595	1.878770846	1.53393	2.179525	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.177215	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730391	-1.7303905	
ln(gij/bij) + ln(Bj/Gj)	-0.364416164	0.287682072	0.148380323	-0.19646	0.44913448	

WOE Ever F (Exposure)

OLNGROUP (OTH_LN)			
	Has no other loan	Has other loan	Total
Goods	620	170	790
	84.35	87.18	
Bads	115	25	140
	15.65	12.82	
Total	735	195	930
gij/bij	5.391304348	6.8	
ln(gij/bij)	1.68478735	1.916922612	
Bj/Gj	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	-0.045603173	0.186532089	

CDP_GROUP			
	0 or missing	GT 0	Total
Goods	499	291	790
	83.44	87.65	
Bads	99	41	140
	16.56	12.35	
Total	598	332	930
gij/bij	5.04040404	7.097560976	
ln(gij/bij)	1.617486246	1.9597512	
Bj/Gj	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	-0.112904277	0.229360678	

AGRGROUP(AGGBORR)	LE 3000	LE 30,000	LE 90,000	GT 90,000	Total
Goods	125	310	198	157	790
	88.03	85.64	81.15	86.26	
Bads	17	52	46	25	140
	11.97	14.36	18.85	13.74	
Total	142	362	244	182	930
gij/bij	7.352941176	5.961538462	4.304347826	6.28	
ln(gij/bij)	1.995100393	1.785328579	1.459625634	1.83736998	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.26470987	0.054938056	-0.270764889	0.106979458	

CXPGROUP (CUSEXP)	0	LE 15,000	LE 60,000	GT 60,000	Total
Goods	190	250	191	159	790
	86.76	87.11	82.33	82.81	
Bads	29	37	41	33	140
	13.24	12.89	17.67	17.19	
Total	219	287	232	192	930
gij/bij	6.551724138	6.756756757	4.658536585	4.818181818	
ln(gij/bij)	1.879728242	1.910543005	1.538701361	1.572396641	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.149337719	0.180152482	-0.191689162	-0.157993882	

BODGROUP (BUS_OD)	0 or missing	LE 5,000	GT 5000	
Goods	451	178	161	790
	83.52	87.68	86.1	
Bads	89	25	26	140
	16.48	12.32	13.9	
Total	540	203	187	930
gij/bij	5.06741573	7.12	6.192307692	
ln(gij/bij)	1.62283097	1.962907725	1.823307827	
Bj/Gj	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	-0.107559553	0.232517203	0.092917304	

TAGGROUP(TOTALAG)	LT 4,000	LE 10,000	LE 40000	LE 100000	GT 100000	Total
Goods	146	113	222	156	153	790
	88.48	88.28	83.15	79.19	88.44	
Bads	19	15	45	41	20	140
	11.52	11.72	16.85	20.81	11.56	
Total	165	128	267	197	173	930
gij/bij	7.684210526	7.533333333	4.933333333	3.804878049	7.65	
ln(gij/bij)	2.039167643	2.019337618	1.596014892	1.336283941	2.034706	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730390523	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.30877712	0.288947095	-0.134375631	-0.394106582	0.304315	

NSMGROUP(NEWSUM)	LE 4000	LE 10000	LE 40000	LE 100000	GT 100000	
Goods	174	123	229	152	112	790
	87.44	88.49	82.97	81.28	86.82	
Bads	25	16	47	35	17	140
	12.56	11.51	17.03	18.72	13.18	
Total	199	139	276	187	129	930
gij/bij	6.96	7.6875	4.872340426	4.342857143	6.588235	
ln(gij/bij)	1.940179474	2.039595633	1.583574402	1.468532459	1.885286	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	0.177215	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730390523	-1.730391	
ln(gij/bij) + ln(Bj/Gj)	0.209788951	0.30920511	-0.146816121	-0.261858063	0.154895	

BLNGROUP	0 or missing	LE 10000	LE 50000	GT 50000	Total
Goods	411	37	165	177	790
	86.34	88.1	83.76	82.33	
Bads	65	5	32	38	140
	13.66	11.9	16.24	17.67	
Total	476	42	197	215	930
gij/bij	6.323076923	7.4	5.15625	4.657894737	
ln(gij/bij)	1.844205945	2.00148	1.640209571	1.538563573	
Bj/Gj	0.17721519	0.17721519	0.17721519	0.17721519	
ln(Bj/Gj)	-1.730390523	-1.730390523	-1.730390523	-1.730390523	
ln(gij/bij) + ln(Bj/Gj)	0.113815422	0.271089477	-0.090180952	-0.19182695	

Appendix 6.3 Bivariate correlation matrices of explanatory variables

	TAGROUP	RYEGROUP	RTNGROUP	PSTGROUP	RTAGROUP	LDOGROUP	RGPGROUP	PNPGROUP	RPLGROUP	RRPGROUP	PGPGROUP	PSDGROUP
TAGROUP	1.00											
RYEGROUP	0.09**	1.00										
RTNGROUP	.	.	1.00									
PSTGROUP	0.03	.34**	0.03	1.00								
RTAGROUP	0.03	0.13**	.	.*	1.00							
LDOGROUP	.	.**	.	.	.07*	1.00						
RGPGROUP	0.07**	0.35**	.**	0.02	.15**	0.00	1.00					
PNPGROUP	.	0.12**	.	.	.52**	.06*	.16**	1.00				
RPLGROUP	0.09**	.26**	.07*	.06*	.17**	.	.24**	.13**	1.00			
RRPGROUP	.	.18**	0.05	0.04	.33**	0.05	0.05	.37**	.07*	1.00		
PGPGROUP	0.08**	.15**	.**	0.02	.09**	.06*	.34**	.17**	.	.10**	1.00	
PSDGROUP	.	.29**	.	0.00	.60**	.07*	.25**	.66**	.17**	.40**	.27**	1.00

	DPRGROUP	BPVGROUP	CPRGROUP	LDOGROUP	AGRGROUP	DYRGROUP	PJSGROUP	ACLGROUP	BSMGROUP	NSMGROUP	OLNGROUP	ODVGROUP
DRPGROUP	1.00											
BPVGROUP	0.18	1.00										
CPRGROUP	-0.01	0.12**	1.00									
LDOGROUP	-0.07*	-0.01	-0.08*	1.00								
AGRGROUP	0.04	0.10**	0.10**	-0.02	1.00							
DYRGROUP	-0.04	0.09**	-0.05	-0.12**	0.03	1.00						
PJSGROUP	-0.05	0.04	0.29**	0.01	0.05	0.08*	1.00					
ACLGROUP	0.03	0.06	0.11**	0.06	0.33**	0.04	0.03	1.00				
BSMGROUP	-0.01	0.04	0.13**	0.01	0.04	0.06	0.15**	-0.02	1.00			
NSMGROUP	0.01	0.13**	0.08*	-0.01	0.58**	-0.03	0.07*	0.31**	0.03	1.00		
OLNGROUP	-0.02	-0.01	0.07*	-0.03	0.14**	-0.03	0.01	0.07*	0.02	0.17**	1.00	
ODVGROUP	0.04	0.09**	0.11**	0.07*	0.25**	0.07*	0.01	0.88**	-0.01	0.27**	0.06	1.00

Appendix to Chapter 8

My E-T model rationalising the results of Chapter 8

Aim of this appendix

This Appendix aims to describe a model I have derived in order to explain some of my empirical findings that I obtained in **Chapter 8**.

Since it was beyond the scope of my PhD (given time and knowledge constraints) to reformulate my Equilibrium-Transitional (E-T) credit rationing model as a mathematical system of equations, I thought it best to describe the framework here because it may be of interest to a reader. However, I would hope on completion of my PhD to develop this model further since I would argue that the model manages to explain some empirical regularities in my data and also reconcile the two mutually exclusive approaches to credit rationing adopted in the literature.

***'E-T'* hypotheses**

I will now attempt to interpret my empirical results by reference to an interpretative model called the *'E-T'* model. This model proposes to rationalise my results in a financial economic framework and it draws on past theoretical work describing 'transitional' and 'equilibrium' credit rationing.

Because my choice of model is influenced by the analysis of credit constraints in **Chapter 8**, I aim to interpret rather than predict my results using the *'E-T' model* that describes first-period borrowing. While aware of the weaknesses of data driven modelling in terms of its lack of independence from the data, there is nevertheless a growing need to make the theoretical models reflect more the reality of the lending contract. If totally divorced from the reality of the lending situation, the model is flawed. To date there is a dichotomy between the theoretical models and the empirical models.

The *'E-T' model* attempts to describe first-period lending based on a number of inputs. I refer to the other models by Jaffee and Russell (1976), Cressy (1996a), Stiglitz and Weiss (1981) and de Meza and Southey (1996) in order to support my assumptions about how banks lend to a first time business borrowers. However, the model is also based on the empirical results that have already been presented as well as my understanding of the lending situation.

While not an exhaustive model that explains all the relationships in my empirical results it attempts to explain the fact that credit constraints are increasing in the amount borrowed *'borr'*, decreasing in collateral amount *'coll'*, relationship *'prevbor'* and the credit history variable *'fin_dif'*. A summary of the relationships I aim to interpret using the *'E-T' model* is presented in **Table 1**.

The structure of this section is as follows. I first describe how the model proposes to deal with the response variable *'con'* used in the data. Then I present the model assumptions. Following this I describe the shape of the supply and demand curves of the model before describing how they can depict credit constraints. Finally I reformulate the model to include interest margins.

Interpretation of the response variable *'con'*

You will recall that my response variable *'con'* indicated that either the business or the bank rejected the loan. Referring back to my theoretical models, TCR representing first-period credit rationing could be the phenomenon we observe when the entrepreneur turns down the loan. On the other hand, ECR is perhaps the event that is observed when the bank rather than the business rejects the loan.

It is assumed that the amount of the collateral offered influences the bank's decision to reject the loan (ECR). Furthermore, the bank would like to minimise its exposure to first time borrowers by lending less than the equilibrium amount until the borrower's credit grade becomes known (TCR). It lends less than the equilibrium amount if the collateral provided is less than the equilibrium level required. The common denominator in this synthesis of the two types of credit rationing is the relationship between collateral level and the response variable. Businesses with higher assets and hence collateral are more likely to receive a loan approaching the size they requested. Businesses with higher assets are also less high risk and consequently less likely to be turned down by a bank than asset impoverished businesses.

To sum up how I aim to interpret my response variable. My ex post rationalisation of the statistical regularities in my data i.e. the likelihood of loan rejection increasing in borrowing amount and risk and decreasing in collateral must combine elements of the ECR models and the TCR models. I need to use a combination of both models in order to capture both facets of the response variable

Like Jaffee and Russell (1976) and Cressy (1996a), I assume that the bank has a perfectly elastic supply of deposits. The bank operates in a perfectly competitive market and does not make monopoly profits.

The following section outlines the assumptions I make about the assets and collateral of the business as well as the relationship between the demand schedule of the borrower to exogenous changes in assets.

Assumptions of the ***'E-T' model***

There are six main components or assumptions, which I will make about first-period borrowing. I will list these below before turning to the model itself.

Assumption 1: All things equal, it is easier repay less than more

Firstly, in agreement with the conclusions of the J-R model, it is easier for the borrower to repay a smaller loan than a larger one. I choose to ignore here the arguments of the Stiglitz Weiss (1981) model that by lending too little, the whole portfolio of the bank is made riskier and default rises as a result. I assume that the business has enough viability to keep itself operating, albeit at a less than optimal rate at least in the short term. Poor risks will default within the short run by not having enough endogenous growth to tide them through the difficult first period.

A number of business start-ups are poor risks and will default in the short term. This means that of the initial cohort of businesses applying for finance in the first round, a number will have defaulted by the time the second round arrives. The short term is defined as the period necessary for a bank to collect sufficient information on the repayment performance of the borrower. The minimum period for the short term is one year because this is the minimum period of time required for the collection of data, which could be used in estimating a performance scorecard. Businesses are scored on their repayment performance in order to receive subsequent increases to their overdraft facility etc. Even within this first year, a bank should have generated some information on the quality of the borrower through monitoring his money transmission accounts (MTAs). An overdraft facility is such an MTA and a borrower who is overshooting his authorised limit is flagged immediately.

According to de Meza and Southey, quoting from Daly (1990), more than 30 percent of new businesses in the UK close within the first three years of their operations. According to another source of UK statistics, under 20 percent of start-ups fail in their first year of trading and over 60 percent in the first 5 years (Barclay's Bank Information Service, 2000).

Assumption 2: *'core asset'* assumption

The third assumption I make is that each borrower has one core asset to offer as collateral to a bank. This assumption is realistic in the case of business start-ups who are in a position offer the land on which their premises is located or the business premises itself (if they own the business premises). Apart from this core asset *Land and Buildings*, they may not have much else to offer a bank as collateral. I assume that a bank finds the administration involved on a core asset comparatively easier and more efficient to administer than a plethora of smaller, non-core assets.

In **Chapter 9**, I present evidence that collateral plays a more important role in first time finance than in subsequent periods. This result is also borne out by Evans and Jovanovic (1989). Such evidence indicates that core assets are taken as a signal of goodwill in the first period while the level of finance is augmented in the second period, often bearing little relation to the magnitude of the initial collateral.

In my own dataset of the 7,671 borrowers, 3,488 borrowers corresponding to 45.5 percent of the sample had their loans collateralised. Of the 3,198 borrowers offering *Land and Buildings* as collateral, only 78 offered a life policy as well. *Land and buildings* therefore represent the core asset. All residual assets are referred to as non-core assets.

The core asset assumption has another additional use apart from simplifying the model. It also helps us deal with the problem that collateral is directly observed in my data while business assets are not.

Since the assets of the business are not observed in my dataset, these cannot be used in lieu of collateral level as an explanatory variable. Collateral can be transformed into an exogenous variable for the decision of the bank to lend or otherwise, if I assume the *'core asset'* assumption. By assuming that the most highly valued, non-specialised asset with the lowest dead-weight cost is used as collateral, the problem of assets not being directly observed while collateral is, is to some extent remedied[1]. By assuming that the borrower posts all his core-assets as collateral, we no longer have a dichotomy between assets and collateral where collateral was a subset of assets. By assuming that core assets are equal to collateral I assume that all the collateral observed in first period lending is equivalent to the full complement of core business assets.

By assuming that the core asset comprises the only collateral offered on a first-period loan (core assets=collateral), the collateral becomes another determinant of the bank's decision to grant a loan or not.

I argue that there are solid a priori reasons for applying this *'core asset'* assumption, including the high proportion of businesses in my TS group, which are secured on one asset as I have mentioned above. Although my model takes precedence over data complexities, I have observed regularities in my data when making my assumptions.

[1] The deadweight cost of collateral is defined as the differential between the asset's in-use value and its liquidation value. In other words, the difference between its first and second best use.

Assumption 3: Initial wealth is used to secure first-period borrowing and not the purchased asset

I make a further assumption here regarding initial wealth. I assume that in the first period a bank is only interested in collateralising a loan based on the starting wealth of the entrepreneur (Evans and Jovanovic, 1989).

This assumption also has an intuitive explanation. Imagine that a start-up or firm without a track record approaches a bank for a loan. A bank could offer him a fully asset backed loan of infinite value and be fully covered by the value of the item purchased in the eventuality of borrower default. However, it is not likely that a bank pursues this policy in first-period lending. Because it is likely that the asset purchased has a high value in its first best use relative to its liquidation value (high dead-weight loss), it can be expected that the bank will opt for collateral which the entrepreneur already has. This existing collateral, in the form of land and buildings or life policies, is expected to have a comparatively lower dead-weight loss than highly specialised plant or machinery. Therefore, the bank reverts to using this *'core asset'* to collateralise the loan.

Assumption 4: I assume collateral to loan value ratios of > 1 to allow slack for second period borrowing. Also this shows conservatism in first period lending

This assumption implies that banks are more conservative in the first rather than second lending periods. I therefore assume higher collateral to loan value ratios. In my model, this conservatism implies that collateral divided by loan amount is greater than 1.

The empirical evidence corroborates my assumption of collateral to value ratios in excess of unity. These ratios are typically high for small firms. Binks et al. (1993) cites a ratio of over unity for 85 percent of UK loans.

A further reason for expected high C/L ratio is that the enterprise believes that it will survive into the second period. The understanding is that it will have its overdraft limit or renegotiated second-period loan, leveraged on the same core asset. In other words, there is some in-built slack in the provision of first period collateral. Rather than pricing collateral to risk, excess collateral will be used to secure second-period borrowing. Rather than the bank increasing the asset requirements in the second period, therefore, it waits to see how the firm will perform in the first period before renegotiating a higher amount of finance.

It could be argued that this understanding should be written into the loan contract. It can be either implicit or explicitly stated in the contract that the bank takes a charge over a proportion of the firm's assets. In reality, default by the enterprise means the ultimate liquidation of the whole asset where the surplus value of the asset has a lower value in its next best use. Therefore, the bank may as well take a charge over the full asset value. It can do this if the understanding between the bank and firm implies that first-period borrowing is an advance on the full amount requested. The residual finance will be extended in the second period subject to the firm meeting its repayment targets. The collateral taken in the first period, therefore pertains to cumulative borrowing in the second period.

It is be possible that the ratio of collateral to value is non-linear with increases in firm size. This would happen if banks imposed a requirement for collateral at a minimum loan size e.g. all loans in excess of £1,000. Above this minimum collateralised loan, with successive increases in loan amount, the proportion of collateral would be falling if larger loans had lower default rates or the cost of administering the collateral exhibited lower per unit costs.

Apart from possible returns to collateral usage affecting the supply curve rather than the demand curve, there are other factors that differentiate the supply from the demand curve. One of these is the dead-weight costs of collateral. The dead-weight cost of collateral relates to the asymmetric evaluation of an asset from the perspective of a banker vis a viz. an entrepreneur. The banker must liquidate the asset in order to realise its value with resulting loss of value while the entrepreneur values the asset more highly in its first-best use[2].

The bank will be more conservative and accordingly more wary of first-period borrowing as evidenced by Bink's empirical analysis of UK small firms, if small firms are more likely to be younger and thence more likely to be involved in first-period borrowing.

Assumption 5: All first-term loans are secured. I examine total exposure rather than loans and overdrafts in isolation.

A final assumption relates how I define borrowing as total exposure.

I assume that overdrafts are also collateralised on the core asset of the business where a floating charge is taken over this asset to secure an overdraft. Although the collateralisation of overdrafts is not as emphasised as the collateralisation of loans in the literature, I assume that overdrafts are to a large extent collateralised for two reasons.

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[2] Deadweight costs should not play a large role in my data because the bank does not accept idiosyncratic assets such as machinery or office equipment as collateral. If it were to accept such specialised assets as collateral there would be a wide gap between the value of the collateral in their first best vis a viz. their second best use. In other words, the deadweight costs of the collateral would be high.

Firstly, these are first time borrowers and are likely to be high risk irrespective of the type of borrowing they take out. For this reason, there is a relatively high need to secure their borrowing.

Secondly, as Berger and Udell (1992) show in their empirical analysis, 53 percent of the 872 lines of credit or L/Cs (equivalent to overdrafts) are secured by collateral. In my sample of the 3,812 working capital loans, the number secured is 1,443 corresponding to 38 percent. Because lines of credit and working capital loans can also be secured, I do not mean the *'E-T' model* to apply only to loan finance but to the total exposure of the firm. This consideration of total business exposure is in line with circumstantial evidence from loan sanctioners at the bank who viewed risk over the whole exposure of the firm.

Assumption 6: The demand of the entrepreneur for finance rises linearly with the level of initial wealth

The assumption is that *a priori* wealthy firms demand a comparatively higher level of first-period finance than demanded by asset poor entrepreneurs. A way of illustrating this assumption is to imagine a comparatively wealthy entrepreneur having £50,000 of core assets and £5,000 of his own cash savings. His poor entrepreneur counterpart has £20,000 of core assets and £2,000 cash savings. In both cases the ratio of their core asset to their own savings is 10:1. I assume a constant describes the ratio between the value of core assets and the savings of the owner. The poor entrepreneur is starting from a lower level than his wealthy counterpart. Being risk adverse, where risk implies business failure and the forfeiture of their collateral, they will not want to undertake to repay a debt they know they cannot realistically service. I assume that the loss of £50,000 worth of collateral to the wealthy entrepreneur is equivalent to the loss of £20,000 worth of collateral to the poor entrepreneur. I also assume that the project is financed by a combination of bank and equity finance where £5,000 plus a £5,000 bank loan will cover a larger initial project than a project costing £2,000 equity plus a £2,000 loan.

Therefore, entrepreneurs operate in a rational way and tailor their expectations regarding the amount of first-period finance they can obtain from the bank on the value of their core assets. Put another way, it would be unreasonable for an entrepreneur with a small life assurance policy to expect a generous first-time loan. Entrepreneurs are risk adverse agents who know that they will forfeit any collateral they post on failing. They therefore request an amount of finance they expect they can hope to service.

Supply and demand curves

I now move on to the model itself. In this section, I will describe the shape of the demand curve and compare it with the structure of the supply curve, which has already been mentioned.

The demand curve describing the trade-off between collateral and amount borrowed is upward sloping for the following reason. According to **Assumption 6**, the demand for finance rises linearly with assets. Given **assumption 2** that assets and collateral are equivalent, it follows that larger firms, with higher levels of assets demand higher levels of finance. However, they post all their core assets as collateral and therefore higher levels of collateral are associated with higher levels of borrowing. You can imagine this as an upward sloping demand schedule because as the asset level and correspondingly collateral increases, so also does the level of borrowing. The demand curve is seen as the upwardly sloping grey line in **Figure 1**. I now move on to describe the supply curve for finance.

The supply curve for finance is upwardly sloping because the bank is willing to supply more finance in exchange for increases in collateral *C*. However, the bank will not supply infinitely large amounts of finance to first-period borrowers. There is therefore a maximum level of loan that the bank is prepared to give to a first-period commercial borrower in the first period of his borrowing. The first-term supply curve should be asymptotic to this maximum first-term loanable level. The first-term supply curve is also be discontinuous above the maximum loanable level indicating that businesses demanding loans in excess of the maximum loanable level are denied finance. No finance is supplied above the maximum loanable amount. Up to that point, there is a positive association between collateral and the amount loaned where larger amounts of collateral are offered larger loans.

Now I relate my description of the supply curve back to **Figure 1**. The first-period supply curve S_1 is described by the black asymptotic function. S_1 is asymptotic to the first-period maximum loanable amount *Lmax*. The supply schedule does not intersect with the demand curve D_1 until the second lending period when the second period supply schedule S_2 intersects the demand schedule D_1 giving an equilibrium loan L^* and equilibrium collateral level C^*. The second period maximum loanable amount is *Lmax2*.

The other feature of the supply curve for finance is that the bank will find increasing returns to collateral use up to a certain level. After this critical level is reached, the returns to collateral usage are negative. For very large amounts of collateral usage, the returns to collateral usage are diminishing. This is because the bank has already reached its maximum loanable amount and any additional collateral will not leverage the same increase in finance. The returns to collateral usage can be seen in the horizontal distance between the supply S_I and demand curves respectively. The two curves converge up to a certain point C_I. Up to the point C_I increases in collateral bring the quantity supplied closer to the quantity demanded. However increases in collateral beyond C_I are not desirable from the entrepreneur's point of view because the horizontal distance between supply and demand grows rapidly as the supply curve becomes progressively flatter. Entrepreneurs offering collateral C^* for a loan of L^* in the first-term will be turned down by the bank because S_I is discontinuous at C^*. In other words, in the first period, the bank is not prepared to lend any loan greater and equal to L^* corresponding to C^* or greater on the entrepreneur's demand curve D_1.

A final feature of the supply curve relates to the dead-weight costs (defined earlier) of collateral usage (see **Assumption 4**). If the bank liquidates collateral, the value realised on sale of the asset (the value in its next best use) is less than that in its first-best use. Also disposal costs can be high and there is a cost involves in advertising the asset for sale as well as a cost involved in recovering the value of the asset from its sale.

In my dataset the dead-weight costs of collateral are assumed to be low because the bank does not accept idiosyncratic assets such as specialised equipment or machinery as loan security. Idiosyncratic assets are expected to have high dead-weight costs. On the other hand, land and buildings or life policies have comparatively lower dead-weight costs. Nevertheless, the dead-weight cost of collateral is seen in the horizontal distance between the 45 degree line (assuming a ratio of unity between collateral and loan value) and the supply curve. At the equilibrium point y the distance is xy[3].

First period-credit constraints; explaining borrower and bank rejection

Let us now observe both TCR and ECR in my model. I first of all take the case of 'transitional credit rationing'. This occurs when the supply of lending falls short of the demand for funding in the first period. However, once the risk status of the borrower becomes known, the bank will supply the full amount in the second period. Bad risks will drop out of the market for funds by the second period. In **Figure 1**, for collateral amounts

[3] Collateral is exogenous and loan amount is endogenous. The reason for this is as follows. The entrepreneur stakes all he has on first-period borrowing in order to get the largest loan possible for his given amount of collateral. Assets (corresponding to collateral in my model) are also assumed to be exogenous in studies by Evans and Jovanovic (1989) and Cressy (1996a)

less than the equilibrium level i.e. $C_1 < C^*$, the demand for finance outstrips the supply of finance $Qd_1 > Qs_1$ and there is equilibrium credit rationing.

Entrepreneurs with sub-optimal levels of assets and therefore collateral are more heavily penalised under TCR in the first period. This is seen in **Figure 1.** For any $C < C_1$, the difference between the quantity demanded and the quantity supplied is greater, the greater the reduction in the level of C. If an entrepreneurs' utility decreases with higher absolute differences between the quantity demanded and the quantity supplied, it follows that with lower levels of C, an entrepreneur is more likely to reject the loan. This is because the amount he receives falls further short of his expectations than the amount he would receive with a higher level of collateral C.

The firm has a choice under 'transitionary credit rationing'. It can either accept the sub-optimal loan in the first period and await further finance in the second period. Alternatively, it can reject the amount of lending Qs offered by the bank in the first period.

If the entrepreneur decides to accept what little the bank has to offer in the first period, the bank makes good the entire shortfall in finance in the second period by shifting the supply curve. The firm is no longer rationed to the same extent at the level of collateral $C_1 < C^*$. We see this shifting of the supply curve from S_1 to S_2 in **Figure 1** where S_1 is the first-period supply curve and S_2 the second period supply curve.

I conclude that entrepreneurs who have more collateral to offer the bank do not experience 'transitional' credit rationing to the extent as entrepreneurs who have less collateral to offer the bank. This is because the gap between the quantity demanded and the quantity supplied should be less, the greater the level of collateral up to a certain point. It follows that entrepreneurs are less willing to reject a loan when it comes closer to their expectations. Therefore, entrepreneurs with more collateral are less willing to reject a loan. Under transitional credit rationing, the likelihood of being turned down P(*'con'*) is less for higher levels of collateral *'coll'*. This is what we witnessed in the empirical results in **Chapter 8**.

I now turn to the other dimension of my response variable *'con'*, where the bank turns down the loan because the bank perceiving the entrepreneur as being too high risk. This time the bank initiates the action to reject the loan rather than the entrepreneur.

I assume that the bank is more inclined to turn down a loan if the entrepreneur asks for too much finance such that the amount requested exceeds the maximum allowable amount and falls above the discontinuity in the first period supply curve. Therefore, with equilibrium credit rationing, the likelihood that (*'con'*) increases with increases in the amount of finance demanded *'borr'*.

How do we interpret the positive relationship between the risk variable *'fin_dif'* in the context of the *'E-T' model*? We can imagine any risk variable as shifting the supply curve to the right such that the bank will request additional collateral to cover the additional risk involved in lending to high risk *hr* firms.

Figure 2 shows the supply curve shifting to the right in order to describe the increased conservatism of the bank in lending to such firms. The amount of collateral that the bank requires for a loan Q_s increases from *Cnr* to *Chr* to reflect the heightened risk of lending to a previous insolvent firm, a firm who has had difficulty meeting past repayments on whom adverse information is reported following a credit bureau search.

A similar effect should be registered for firms who have had no previous borrowing experience from the bank (*'prevbor=0'*). Such higher risk firms should be required to provide additional collateral. Given that there is a greater disparity between the demand D_1 and new supply curve S_2 under the riskier regime (greater vertical distance between the curves measuring the loan amount supplied/demanded for a given level of collateral), it follows that the firm is more inclined to turn down such a loan all things equal.

It may even be the case that the maximum loanable amount *Lmax* also shifts down such that there is also a higher rejection rate (equilibrium credit rationing) for higher risk firms. Firms asking for *Qd* under the original risk regime *nr* would be rejected under the higher risk regime *hr* because the amount demanded *Qd* lies above the new supply curve S_2.

Summary of my *'E-T' model*

I now summarise my interpretation of first-period lending (**Table 1**) and relate it back to my empirical results.

The likelihood of a borrower's loan being turned down (*'con'*) should be decreasing in the amount of collateral provided according to my ex post rationalisation of first-period lending. This is because higher collateral (up to a certain point) should reduce the distance between the supply and demand curves and bring the entrepreneur's expectations of loan size closer to those of the bank. Therefore there is a lower likelihood that the entrepreneur will turn down the loan. Therefore, collateral reduces 'transitionary' credit rationing. In my empirical results presented in **Chapter 8**, we see that collateral does play such a role in reducing the likelihood that the loan is rejected up to a certain point in the first period. However no amount of finance L^* is given in exchange for C^* above C^* because the first-period supply curve S_1 is discontinuous at C^*.

The likelihood that a loan is turned down is higher, the higher the amount of finance *'borr'* demanded by the firm. As we move along the demand curve for first-period borrowing, we see that after a certain point (maximum loanable amount which is less than the second period equilibrium amount L^*) the bank will refuse to supply any loan. The bank therefore rejects loans that are in excess of *Lmax*. This is equilibrium credit rationing. In my data we see that the likelihood that (*'con'*) is increasing in the amount requested '*borr*'.

The likelihood that a loan is turned down should also be decreasing in the risk of a loan according to my rationalisation of first-period lending. We see that this is the case where the business risk variable '*fin_dif*' is positively related to loan rejections.

Finally, borrower risk should be attenuated if the bank knows more about the entrepreneur's credit status. Since the bank knows more about the entrepreneur's creditworthiness over the length of a business-bank relationship, it follows that borrower risk should be negatively related with the length of a business-bank relationship. Alternatively, entrepreneurs who have exhibited past borrowing '*prevbor=1*' with the bank should have lower risk and consequently show a lower likelihood of having their loans turned down. We see that this is the case and my empirical results show that the variable *'prevbor'* and '*prevbor=1*' have negatively signed coefficients.

Table 1	**Predictions of *'E-T'* model***
Collateral level *'coll'*	Negative
Amount requested *'borr'*	Positive
Risk variable *'fin_dif'*	Positive
Relationship variables *'prevbor'*, *'prevbor=1'*	Negative
Other control variables	Negative if control variables negatively related to risk

*All conjectured relationships are with the response variable *'con'* measuring whether the business loan was rejected

Figure 1 **Demand and supply schedules for first-period loans**

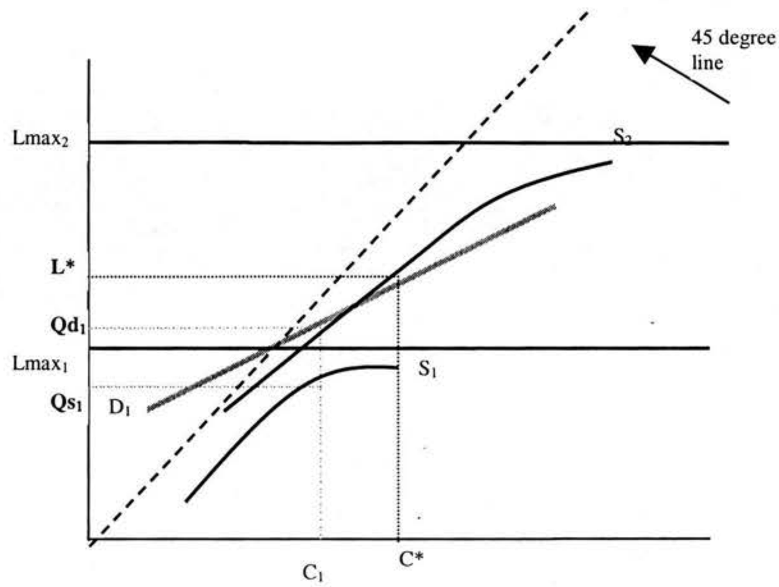

Figure 2 **Response to an increase in loan risk**